

Handbook of
PARAMETRIC and
NONPARAMETRIC
STATISTICAL PROCEDURES
SECOND EDITION

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STATISTICAL PROCEDURES
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Preface

Like the first edition, the second edition of the **Handbook of Parametric and Nonparametric Statistical Procedures** is designed to provide researchers, teachers, and students with a comprehensive reference book in the areas of parametric and nonparametric statistics. The addition of a large amount of new material (250 pages) makes the Handbook unparalleled in terms of its coverage of material in the field of statistics. Rather than being directed at a limited audience, the Handbook is intended for individuals who are involved in a broad spectrum of academic disciplines encompassing the fields of mathematics/statistics, the social and biological sciences, business, and education. My philosophy in writing both this and the previous edition was to create a reference book on parametric and nonparametric statistical procedures that I (as well as colleagues and students I have spoken with over the years) have always wanted, yet could never find. To be more specific, my primary goal was to produce a comprehensive reference book on univariate and bivariate statistical procedures which covers a scope of material that extends far beyond that which is covered in any single available source. It was essential that the book be applications oriented, yet at the same time that it address relevant theoretical and practical issues which are of concern to the sophisticated researcher. In addition, I wanted to write a book that is accessible to people who have a limited knowledge of statistics, as well as those who are well versed in the subject. I believe I have achieved these goals, and on the basis of this I believe that the **Handbook of Parametric and Nonparametric Statistical Procedures** will continue to serve as an invaluable resource for people in multiple academic disciplines who conduct research, are involved in teaching, or are presently in the process of learning statistics.

I am not aware of any applications-oriented book that provides in-depth coverage of as many statistical procedures as the number that are covered in the **Handbook of Parametric and Nonparametric Statistical Procedures**. Inspection of the **Table of Contents** and **Index** should confirm the scope of material covered in the book. A unique feature of the Handbook, which distinguishes it from other reference books on statistics, is that it provides the reader with a practical guide that emphasizes application over theory. Although the book will be of practical value to statistically sophisticated individuals who are involved in research, it is also accessible to those who lack the theoretical and/or mathematical background required for understanding the material documented in more conventional statistics reference books. Since a major goal of the book is to serve as a practical guide, emphasis is placed on decision making with respect to which test is most appropriate to employ in evaluating a specific design. Within the framework of being user-friendly, clear computational guidelines, accompanied by easy-to-understand examples, are provided for all procedures.

One should not, however, get the impression that the **Handbook of Parametric and Nonparametric Statistical Procedures** is little more than a cookbook. In point of fact, the design of the Handbook is such that within the framework of each of the statistical procedures which are covered, in addition to the basic guidelines for decision making and computation, substantial in-depth discussion is devoted to a broad spectrum of practical and theoretical issues, many of which are not discussed in conventional statistics books. Inclusion of the latter material ensures that the Handbook will serve as an invaluable resource for those who are sophisticated as well as unsophisticated in statistics.

In order to facilitate its usage, most of the procedures contained in the Handbook are organized within a standardized format. Specifically, for most of the procedures the following information is provided:

I. Hypothesis evaluated with test and relevant background information The first part of this section provides a general statement of the hypothesis evaluated with the test. This is followed by relevant background information on the test such as the following: a) Information regarding the experimental design for which the test is appropriate; b) Any assumptions underlying the test which, if violated, would compromise its reliability; and c) General information on other statistical procedures that are related to the test.

II. Example This section presents a description of an experiment, with an accompanying data set (or in some instances two experiments utilizing the same data set), for which the test will be employed. All examples employ **small sample sizes**, as well as **integer data** consisting of **small numbers**, in order to facilitate the reader's ability to follow the computational procedures to be described in Section IV.

III. Null versus alternative hypotheses This section contains both a **symbolic** and **verbal** description of the statistical hypotheses evaluated with the test (i.e., the **null hypothesis** versus the **alternative hypothesis**). It also states the form the data will assume when the null hypothesis is supported, as opposed to when one or more of the possible alternative hypotheses are supported.

IV. Test computations This section contains a step-by-step description of the procedure for computing the test statistic. The computational guidelines are clearly outlined in reference to the data for the example(s) presented in Section II.

V. Interpretation of the test results This section describes the protocol for evaluating the computed test statistic. Specifically: a) It provides clear guidelines for employing the appropriate table of critical values to analyze the test statistic; b) Guidelines are provided delineating the relationship between the tabled critical values and when a researcher should retain the null hypothesis, as opposed to when the researcher can conclude that one or more of the possible alternative hypotheses are supported; c) The computed test statistic is interpreted in reference to the example(s) presented in Section II; and d) In instances where a parametric and nonparametric test can be used to evaluate the same set of data, the results obtained using both procedures are compared with one another, and the relative power of both tests is discussed in this section and/or in Section VI.

VI. Additional analytical procedures for the test and/or related tests Since many of the tests described in the Handbook have additional analytical procedures associated with them, such procedures are described in this section. Many of these procedures are commonly employed (such as comparisons conducted following an analysis of variance), while others are used and/or discussed less frequently (such as the tie correction employed for the large sample normal approximation of many nonparametric test statistics). Many of the analytical procedures covered in Section VI are not discussed (or if so, only discussed briefly) in other books. Some representative topics which are covered in Section VI are planned versus unplanned comparison procedures, measures of association for inferential statistical tests, computation of confidence intervals, and computation of power. In addition to the aforementioned material, for many of the tests there is additional discussion of other statistical procedures that are directly related to the test under discussion. In instances where two or more tests produce equivalent results, examples are provided which clearly demonstrate the equivalency of the procedures.

VII. Additional discussion of the test Section VII discusses theoretical concepts and issues, as well as practical and procedural issues that are relevant to a specific test. In some instances where a subject is accorded brief coverage in the initial material presented on the test, the reader is alerted to the fact that the subject is discussed in greater depth in Section VII. Many of the issues discussed in this section are topics that are generally not covered in other books, or if they are, they are only discussed briefly. Among the topics covered in Section VII is additional discussion of the relationship between a specific test and other tests that are related to it. Section

VII also provides bibliographic information on less commonly employed alternative procedures that can be used to evaluate the same design for which the test under discussion is used.

VIII. Additional examples illustrating the use of the test This section provides descriptions of one or more additional experiments for which a specific test is applicable. For the most part, these examples employ the **same data set** as that in the original example(s) presented in Section II for that test. By virtue of using standardized data for most of the examples, the material for a test contained in Section IV (**Test computations**) and Section V (**Interpretation of the test results**) will be applicable to most of the additional examples. Because of this, the reader is able to focus on common design elements in various experiments which indicate that a given test is appropriate for use with a specific type of design.

IX. Addendum At the conclusion of the discussion of a number of tests an **Addendum** has been included that describes one or more related tests that are not discussed in Section VI. As an example, the **Addendum** of the **between-subjects factorial analysis of variance** contains an overview and computational guidelines for the **factorial analysis of variance for a mixed design** and the **within-subjects factorial analysis of variance**.

References This section provides the reader with a listing of primary and secondary source material on each test.

Endnotes At the conclusion of most tests, a detailed endnotes section contains additional useful information that further clarifies or expands upon material discussed in the main text.

The first edition of the **Handbook of Parametric and Nonparametric Statistical Procedures** was comprised of an **Introduction** followed by 26 chapters, each of which documented a specific inferential statistical test (as well as related tests) or measure of correlation/association.

The general label **Test** was used (and is used in this edition) for all procedures described in the book (i.e., inferential tests as well as measures of correlation/association). In addition to the **Introduction**, the second edition of the Handbook contains 32 chapters. A chapter describing in detail each of the following six tests has been added the second edition: a) **The single-sample test for evaluating population skewness (Test 4)**; b) **The single-sample test for evaluating population kurtosis (Test 5)** (**The D'Agostino–Pearson test of normality (Test 5A)** is also described in this chapter); c) **The Kolmogorov–Smirnov goodness-of-fit test for a single sample (Test 7)** (**The Lilliefors test for normality (Test 7a)** is also described in this chapter); d) **The Kolmogorov–Smirnov test for two independent samples (Test 13)**; e) **The Moses test for equal variability (Test 15)**; and f) **The van der Waerden normal-scores test for k independent samples (Test 23)**. In addition to the aforementioned tests, a substantial amount of new material has been added to tests that were included in the first edition. Chapters/Tests included in the first edition are noted below, indicating subject matter that has been added to the second edition.

Introduction: Description and computation of the **coefficient of variation**; extensive coverage of **skewness** and **kurtosis**, including description and computation of the **Pearsonian coefficient of skewness**, the g_1 and $\sqrt{b_1}$ measures of skewness, and the g_2 and b_2 measures of kurtosis.

The chi-square goodness-of-fit test (Test 8): Illustration of the use of the **chi-square goodness-of-fit test** for assessing goodness-of-fit for a normal population distribution; discussion of **Cohen's w index** for computing the power of the **chi-square goodness-of-fit test**; description of **heterogeneity chi-square analysis**. Two additional examples have been added to this chapter to illustrate the new material.

The binomial sign test for a single sample (Test 9): Discussion of **Cohen's g index** for computing the power of the **binomial sign test for a single sample**; evaluating goodness-of-fit for a binomial distribution. An **Addendum** has been added that provides comprehensive coverage of the following discrete probability distributions: **multinomial distribution**; **negative**

binomial distribution; hypergeometric distribution; Poisson distribution; and matching distribution. Twelve additional examples have been added to this chapter to illustrate the new material.

The single-sample runs test (and other tests of randomness) (Test 10): The extension of the **runs test** to data with more than two categories is described. The **runs test for serial randomness (Test 10a)** has been added to this chapter. There is additional discussion of the concept of randomness. An **Addendum** has been added that describes in detail the generation of **pseudorandom numbers** — specifically, the following methods are described: the **midsquare method**, the **midproduct method**, and the **linear congruential method**. The **Addendum** also provides detailed coverage of the following alternative tests of randomness: **The frequency test (Test 10b)**, **The gap test (Test 10c)**, **The poker test (Test 10d)**, **The maximum test (Test 10e)**, and **The mean square successive difference test (Test 10f)**. One additional example has been added to this chapter to illustrate the new material. In addition, a standardized data set is evaluated with four of the aforementioned tests of randomness.

The *t* test for two independent samples (Test 11): Comprehensive discussion of **outliers** (including **Test 11e: Procedures for identifying outliers**), **robust statistical procedures**, and **data transformation** (description of and computational examples illustrating the **square root**, **logarithmic**, **reciprocal**, and **arcsine transformations**); discussion of **Hotelling's T^2** .

The Mann–Whitney *U* test (Test 12): An **Addendum** has been added that provides comprehensive coverage of **computer-intensive/data-driven statistical procedures/resampling statistics**. The following topics are discussed in the **Addendum: Randomization and permutation tests** (including **The randomization test for two independent samples (Test 12a)**, **The bootstrap (Test 12b)**, and **The jackknife (Test 12c)**). Two additional examples have been added to this chapter to illustrate the new material.

The chi-square test for $r \times c$ tables (Test 16): Discussion of **Cohen's w and h indices** for computing the power of the **chi-square test for $r \times c$ tables** and the **z test for two independent proportions (Test 16d)**; **heterogeneity chi-square analysis for 2×2 contingency tables**; expanded coverage of the **odds ratio (Test 16j)** (including discussion of the concept of **relative risk**, **test of significance for an odds ratio (Test 16j-a)**, and computation of a confidence interval for an **odds ratio**); discussion of **Simpson's Paradox**; analysis of **multidimensional contingency tables**. Three additional examples have been added to this chapter to illustrate the new material.

The McNemar test (Test 20): An **Addendum** has been added that describes **The Bowker test of symmetry (Test 20a)**. One additional example has been added to this chapter to illustrate the new material.

The single-factor between-subjects analysis of variance (Test 21): Discussion of **Cohen's f index** employed in computing the power and magnitude of treatment effect for the **single-factor between-subjects analysis of variance**; discussion of **multivariate analysis of variance (MANOVA)**. An **Addendum** has been added that provides comprehensive coverage of the **single-factor between-subjects analysis of covariance (Test 21j)**. One additional example has been added to this chapter to illustrate the new material.

The Kruskal–Wallis one-way analysis of variance by ranks (Test 22): Discussion of an alternative pairwise multiple comparison procedure.

The single-factor within-subjects analysis of variance (Test 24): Revised equations for computing the **omega squared** statistic for magnitude of treatment effect; discussion of **Cohen's f index** employed in computing the power and magnitude of treatment effect for the **single-factor within-subjects analysis of variance**; discussion of the **Latin square design**.

The single-factor between-subjects factorial analysis of variance (Test 27): Revised equations for computing the **omega squared** statistic for magnitude of treatment effect; discussion

of **Cohen's f index** employed in computing the power and magnitude of treatment effect for the single-factor between-subjects factorial analysis of variance.

The Pearson product-moment correlation coefficient (Test 28): The following material has been added to the **Addendum: Nonmathematical descriptions of the following multivariate procedures: Factor analysis, canonical correlation, discriminant analysis, and logistic regression; meta-analysis and related topics.** (This section contains a comprehensive discussion of **meta-analysis** and includes a description of the following meta-analytic procedures: **Test 28n: Procedure for comparing k studies with respect to significance level; Test 28o: The Stouffer procedure for obtaining a combined significance level for k studies; Test 28p: Procedure for comparing k studies with respect to effect size; Test 28q: Procedure for obtaining a combined effect size for k studies.** This section also discusses Jacob Cohen's indices for the power computation of various tests, and the controversy over the conventional significance test based hypothesis testing model versus the minimum-effect hypothesis testing model.) One additional example has been added to this chapter to illustrate the new material.

In addition to the aforementioned topics, the second edition provides expanded information on the **asymptotic relative efficiency of nonparametric statistical procedures.** All in all, 25 new tests have been added to the second edition along with 32 additional examples to illustrate the new material.

Although it is not a prerequisite, the **Handbook of Parametric and Nonparametric Statistical Procedures** is designed to be used by those who have a basic familiarity with descriptive statistics and experimental design. Prior familiarity with the latter subject matter will facilitate one's ability to use the book efficiently. In order to insure that the reader has familiarity with these topics, an **Introduction** has been included which provides a general overview of descriptive statistics and experimental design. Following the **Introduction**, the reader is provided with guidelines and decision tables for selecting the appropriate statistical test for evaluating a specific experimental design. The **Handbook of Parametric and Nonparametric Statistical Procedures** can be used as a reference book or it can be employed as a textbook in undergraduate and graduate courses that are designed to cover a broad spectrum of parametric and/or non-parametric statistical procedures.

The author would like to express his gratitude to a number of people who helped make this book a reality. First, I would like to thank Tim Pletscher of CRC Press for his confidence in and support of the first edition of the Handbook. Special thanks are due to Bob Stern, the mathematics editor at CRC Press, who suggested a second edition. Without his efforts and encouragement this book would not have become a reality. Sylvia Wood of CRC Press deserves thanks for overseeing the production of the final product. I am also indebted to Glena Ames who did an excellent job preparing the copy-ready manuscript. Finally, I must express my appreciation to my wife Vicki and daughter Emily, who both endured and tolerated the difficulties associated with a project of this magnitude.

David Sheskin

To Vicki and Emily

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- II. Example
- III. Null versus Alternative Hypotheses
- IV. Test Computations
- V. Interpretation of the Test Results
- VI. Additional Analytical Procedures for the Siegel–Tukey Test for Equal Variability and/or Related Tests
 1. The normal approximation of the Siegel–Tukey test statistic for large sample sizes
 2. The correction for continuity for the normal approximation of the Siegel–Tukey test for equal variability
 3. Tie correction for the normal approximation of the Siegel–Tukey test statistic
 4. Adjustment of scores for the Siegel–Tukey test for equal variability when $\theta_1 \neq \theta_2$
- VII. Additional Discussion of the Siegel–Tukey Test for Equal Variability
 1. Analysis of the homogeneity of variance hypothesis for the same set of data with both a parametric and nonparametric test, and the power-efficiency of the Siegel–Tukey Test for Equal Variability
 2. Alternative nonparametric tests of dispersion
- VIII. Additional Examples Illustrating the Use of the Siegel–Tukey Test for Equal Variability

Test 15. The Moses Test for Equal Variability

- I. Hypothesis Evaluated with Test and Relevant Background Information
- II. Example
- III. Null versus Alternative Hypotheses
- IV. Test Computations
- V. Interpretation of the Test Results
- VI. Additional Analytical Procedures for the Moses Test for Equal Variability and/or Related Tests
 1. The normal approximation of the Moses test statistic for large sample sizes
- VII. Additional Discussion of the Moses Test for Equal Variability

1. Power-efficiency of the Moses Test for equal variability
 2. Issue of repetitive resampling
 3. Alternative nonparametric tests of dispersion
- VIII. Additional Examples Illustrating the Use of the Moses Test for Equal Variability

Test 16. The Chi-Square Test for $r \times c$ Tables [Test 16a: The Chi-Square Test for Homogeneity; Test 16b: The Chi-Square Test of Independence (employed with a single sample)]

- I. Hypothesis Evaluated with Test and Relevant Background Information
- II. Examples
- III. Null versus Alternative Hypotheses
- IV. Test Computations
- V. Interpretation of the Test Results
- VI. Additional Analytical Procedures for the Chi-Square Test for $r \times c$ Tables and/or Related Tests
 1. Yates' correction for continuity
 2. Quick computational equation for a 2×2 table
 3. Evaluation of a directional alternative hypothesis in the case of a 2×2 contingency table
 4. **Test 16c: The Fisher exact test**
 5. **Test 16d: The z test for two independent proportions**
 6. Computation of a confidence interval for a difference between proportions
 7. **Test 16e: The median test for independent samples**
 8. Extension of the chi-square test for $r \times c$ tables to contingency tables involving more than two rows and/or columns, and associated comparison procedures
 9. The analysis of standardized residuals
 10. Sources for computing the power of the chi-square test for $r \times c$ tables
 11. Heterogeneity chi-square analysis for a 2×2 contingency table
 12. Measures of association for $r \times c$ contingency tables (**Test 16f: The contingency coefficient; Test 16g: The phi coefficient; Test 16h: Cramér's phi coefficient; Test 16i: Yule's Q ; Test 16j: The odds ratio** (and the concept of **relative risk; Test 16j-a: Test of significance for an odds ratio** and computation of a confidence interval for an odds ratio)
- VII. Additional Discussion of the Chi-Square Test for $r \times c$ Tables
 1. Simpson's Paradox
 2. Analysis of multidimensional contingency tables
- VIII. Additional Examples Illustrating the Use of the Chi-Square Test for $r \times c$ Tables

Inferential Statistical Tests Employed with Two Dependent Samples (and Related Measures of Association/Correlation)

Test 17. The t Test for Two Dependent Samples

- I. Hypothesis Evaluated with Test and Relevant Background Information
- II. Example
- III. Null versus Alternative Hypotheses
- IV. Test Computations
- V. Interpretation of the Test Results
- VI. Additional Analytical Procedures for the t Test for Two Dependent Samples and/or Related Tests
 1. Alternative equation for the t test for two dependent samples
 2. The equation for the t test for two dependent samples when a value for a difference other than zero is stated in the null hypothesis
 3. **Test 17a: The t test for homogeneity of variance for two dependent samples:** Evaluation of the homogeneity of variance assumption of the t test for two dependent samples
 4. Computation of the power of the t test for two dependent samples and the application of **Test 17b: Cohen's d index**
 5. Measure of magnitude of treatment effect for the t test for two dependent samples: **Omega squared (Test 17c)**
 6. Computation of a confidence interval for the t test for two dependent samples
 7. **Test 17d: Sandler's A test**
 8. **Test 17e: The z test for two dependent samples**
- VII. Additional Discussion of the t Test for Two Dependent Samples
 1. The use of matched subjects in a dependent samples design
 2. Relative power of the t test for two dependent samples and the t test for two independent samples
 3. Counterbalancing and order effects
 4. Analysis of a before-after design with the t test for two dependent samples
- VIII. Additional Example Illustrating the Use of the t Test for Two Dependent Samples

Test 18. The Wilcoxon Matched-Pairs Signed-Ranks Test

- I. Hypothesis Evaluated with Test and Relevant Background Information
- II. Example
- III. Null versus Alternative Hypotheses
- IV. Test Computations
- V. Interpretation of the Test Results
- VI. Additional Analytical Procedures for the Wilcoxon Matched-Pairs Signed-Ranks Test and/or Related Tests
 1. The normal approximation of the Wilcoxon T statistic for large sample sizes

2. The correction for continuity for the normal approximation of the Wilcoxon matched-pairs signed-ranks test
3. Tie correction for the normal approximation of the Wilcoxon test statistic
4. Sources for computing a confidence interval for the Wilcoxon matched-pairs signed-ranks test
- VII. Additional Discussion of the Wilcoxon Matched-Pairs Signed-Ranks Test
 1. Power-efficiency of the Wilcoxon matched-pairs signed-ranks test
 2. Alternative nonparametric procedures for evaluating a design involving two dependent samples
- VIII. Additional Examples Illustrating the Use of the Wilcoxon Matched-Pairs Signed-Ranks Test

Test 19. The Binomial Sign Test for Two Dependent Samples

- I. Hypothesis Evaluated with Test and Relevant Background Information
- II. Example
- III. Null versus Alternative Hypotheses
- IV. Test Computations
- V. Interpretation of the Test Results
- VI. Additional Analytical Procedures for the Binomial Sign Test for Two Dependent Samples and/or Related Tests
 1. The normal approximation of the binomial sign test for two dependent samples with and without a correction for continuity
 2. Computation of a confidence interval for the binomial sign test for two dependent samples
 3. Sources for computing the power of the binomial sign test for two dependent samples, and comments on asymptotic relative efficiency of the test
- VII. Additional Discussion of the Binomial Sign Test for Two Dependent Samples
 1. The problem of an excessive number of zero difference scores
 2. Equivalency of the Friedman two-way analysis variance by ranks and the binomial sign test for two dependent samples when $k = 2$
- VIII. Additional Examples Illustrating the Use of the Binomial Sign Test for Two Dependent Samples

Test 20. The McNemar Test

- I. Hypothesis Evaluated with Test and Relevant Background Information
- II. Examples
- III. Null versus Alternative Hypotheses
- IV. Test Computations
- V. Interpretation of the Test Results

- VI. Additional Analytical Procedures for the McNemar Test and/or Related Tests
 - 1. Alternative equation for the McNemar test statistic based on the normal distribution
 - 2. The correction for continuity for the McNemar test
 - 3. Computation of the exact binomial probability for the McNemar test model with a small sample size
 - 4. Additional analytical procedures for the McNemar test
- VII. Additional Discussion of the McNemar Test
 - 1. Alternative format for the McNemar test summary table and modified test equation
 - 2. Alternative nonparametric procedures for evaluating a design with two dependent samples involving categorical data
- VIII. Additional Examples Illustrating the Use of the McNemar Test
- IX. Addendum
 - 1. Extension of the McNemar test model beyond 2×2 contingency tables (**Test 20a: The Bowker test of symmetry**)

Inferential Statistical Tests Employed with Two or More Independent Samples (and Related Measures of Association/Correlation)

Test 21. The Single-Factor Between-Subjects Analysis of Variance

- I. Hypothesis Evaluated with Test and Relevant Background Information
- II. Example
- III. Null versus Alternative Hypotheses
- IV. Test Computations
- V. Interpretation of the Test Results
- VI. Additional Analytical Procedures for the Single-Factor Between-Subjects Analysis of Variance and/or Related Tests
 - 1. Comparisons following computation of the omnibus F value for the single-factor between-subjects analysis of variance (Planned versus unplanned comparisons; Simple versus complex comparisons; Linear contrasts; Orthogonal comparisons; **Test 21a: Multiple t tests/Fisher's LSD test; Test 21b: The Bonferroni–Dunn test; Test 21c: Tukey's HSD test; Test 21d: The Newman–Keuls test; Test 21e: The Scheffé test; Test 21f: The Dunnett test**; Additional discussion of comparison procedures and final recommendations; The computation of a confidence interval for a comparison)
 - 2. Comparing the means of three or more groups when $k \geq 4$
 - 3. Evaluation of the homogeneity of variance assumption of the single-factor between-subjects analysis of variance
 - 4. Computation of the power of the single-factor between-subjects analysis of variance

5. Measures of magnitude of treatment effect for the single-factor between-subjects analysis of variance: **Omega squared (Test 21g)**, **Eta squared (Test 21h)**, and **Cohen's f index (Test 21i)**
6. Computation of a confidence interval for the mean of a treatment population
- VII. Additional Discussion of the Single-Factor Between-Subjects Analysis of Variance
 1. Theoretical rationale underlying the single-factor between-subjects analysis of variance
 2. Definitional equations for the single-factor between-subjects analysis of variance
 3. Equivalency of the single-factor between-subjects analysis of variance and the t test for two independent samples when $k = 2$
 4. Robustness of the single-factor between-subjects analysis of variance
 5. Fixed-effects versus random-effects models for the single-factor between-subjects analysis of variance
 6. Multivariate analysis of variance (MANOVA)
- VIII. Additional Examples Illustrating the Use of the Single-Factor Between-Subjects Analysis of Variance
- IX. Addendum
 1. **Test 21j: The Single-Factor Between-Subjects Analysis of Covariance**

Test 22. The Kruskal–Wallis One-Way Analysis of Variance by Ranks

- I. Hypothesis Evaluated with Test and Relevant Background Information
- II. Example
- III. Null versus Alternative Hypotheses
- IV. Test Computations
- V. Interpretation of the Test Results
- VI. Additional Analytical Procedures for the Kruskal–Wallis One-Way Analysis of Variance by Ranks and/or Related Tests
 1. Tie correction for the Kruskal–Wallis one-way analysis of variance by ranks
 2. Pairwise comparisons following computation of the test statistic for the Kruskal–Wallis one-way analysis of variance by ranks
- VII. Additional Discussion of the Kruskal–Wallis One-Way Analysis of Variance by Ranks
 1. Exact tables of the Kruskal–Wallis distribution
 2. Equivalency of the Kruskal–Wallis one-way analysis of variance by ranks and the Mann–Whitney U test when $k = 2$
 3. Power-efficiency of the Kruskal–Wallis one-way analysis of variance by ranks
 4. Alternative nonparametric rank-order procedures for evaluating a design involving k independent samples

VIII. Additional Examples Illustrating the Use of the Kruskal–Wallis One-Way Analysis of Variance by Ranks

Test 23. The Van der Waerden Normal-Scores Test for k Independent samples

- I. Hypothesis Evaluated with Test and Relevant Background Information
- II. Example
- III. Null versus Alternative Hypotheses
- IV. Test Computations
- V. Interpretation of the Test Results
- VI. Additional Analytical Procedures for the van der Waerden Normal-Scores Test for k Independent Samples
 1. Pairwise comparisons following computation of the test statistic for the van der Waerden normal-scores test for k independent samples
- VII. Additional Discussion of the van der Waerden Normal-Scores Test for k Independent Samples
 1. Alternative normal-scores tests
- VIII. Additional Examples Illustrating the Use of the van der Waerden Normal-Scores Test for k Independent Samples

Inferential Statistical Tests Employed with Two or More Dependent Samples (and Related Measures of Association/Correlation)

Test 24. The Single-Factor Within-Subjects Analysis of Variance

- I. Hypothesis Evaluated with Test and Relevant Background Information
- II. Example
- III. Null versus Alternative Hypotheses
- IV. Test Computations
- V. Interpretation of the Test Results
- VI. Additional Analytical Procedures for the Single-Factor Within-Subjects Analysis of Variance and/or Related Tests
 1. Comparisons following computation of the omnibus F value for the single-factor within-subjects analysis of variance (**Test 24a: Multiple t tests/Fisher's LSD test; Test 24b: The Bonferroni–Dunn test; Test 24c: Tukey's HSD test; Test 24d: The Newman–Keuls test; Test 24e: The Scheffé test; Test 24f: The Dunnett test**; The computation of a confidence interval for a comparison; Alternative methodology for computing MS_{res} for a comparison)
 2. Comparing the means of three or more conditions when $k \geq 4$
 3. Evaluation of the sphericity assumption underlying the single-factor within-subjects analysis of variance
 4. Computation of the power of the single-factor within-subjects analysis of variance

5. Measures of magnitude of treatment effect for the single-factor within-subjects analysis of variance: **Omega squared (Test 24g)** and **Cohen's f index (Test 24h)**
6. Computation of a confidence interval for the mean of a treatment population
- VII. Additional Discussion of the Single-Factor Within-Subjects Analysis of Variance
 1. Theoretical rationale underlying the single-factor within-subjects analysis of variance
 2. Definitional equations for the single-factor within-subjects analysis of variance
 3. Relative power of the single-factor within-subjects analysis of variance and the single-factor between-subjects analysis of variance
 4. Equivalency of the single-factor within-subjects analysis of variance and the t test for two dependent samples when $k = 2$
 5. The Latin Square design
- VIII. Additional Examples Illustrating the Use of the Single-Factor Within-Subjects Analysis of Variance

Test 25. The Friedman Two-Way Analysis of Variance by Ranks

- I. Hypothesis Evaluated with Test and Relevant Background Information
- II. Example
- III. Null versus Alternative Hypotheses
- IV. Test Computations
- V. Interpretation of the Test Results
- VI. Additional Analytical Procedures for the Friedman Two-Way Analysis Variance by Ranks and/or Related Tests
 1. Tie correction for the Friedman two-way analysis variance by ranks
 2. Pairwise comparisons following computation of the test statistic for the Friedman two-way analysis of variance by ranks
- VII. Additional Discussion of the Friedman Two-Way Analysis Variance by Ranks
 1. Exact tables of the Friedman distribution
 2. Equivalency of the Friedman two-way analysis variance by ranks and the binomial sign test for two dependent samples when $k = 2$
 3. Power-efficiency of the Friedman two-way analysis variance by ranks
 4. Alternative nonparametric rank-order procedures for evaluating a design involving k dependent samples
 5. Relationship between the Friedman two-way analysis of variance by ranks and Kendall's coefficient of concordance
- VIII. Additional Examples Illustrating the Use of the Friedman Two-Way Analysis of Variance by Ranks

Test 26. The Cochran Q Test

- I. Hypothesis Evaluated with Test and Relevant Background Information
- II. Example
- III. Null versus Alternative Hypotheses
- IV. Test Computations
- V. Interpretation of the Test Results
- VI. Additional Analytical Procedures for the Cochran Q Test and/or Related Tests
 1. Pairwise comparisons following computation of the test statistic for the Cochran Q test
- VII. Additional Discussion of the Cochran Q Test
 1. Issues relating to subjects who obtain the same score under all of the experimental conditions
 2. Equivalency of the Cochran Q test and the McNemar test when $k = 2$
 3. Alternative nonparametric procedures for categorical data for evaluating a design involving k dependent samples
- VIII. Additional Examples Illustrating the Use of the Cochran Q Test

Inferential Statistical Test Employed with Factorial Design (and Related Measures of Association/Correlation)

Test 27. The Between-Subjects Factorial Analysis of Variance

- I. Hypothesis Evaluated with Test and Relevant Background Information
- II. Example
- III. Null versus Alternative Hypotheses
- IV. Test Computations
- V. Interpretation of the Test Results
- VI. Additional Analytical Procedures for the Between-Subjects Factorial Analysis of Variance and/or Related Tests
 1. Comparisons following computation of the F values for the between-subjects factorial analysis of variance (**Test 27a: Multiple t tests/Fisher's LSD test; Test 27b: The Bonferroni–Dunn test; Test 27c: Tukey's HSD test; Test 27ad: The Newman–Keuls test; Test 27e: The Scheffé test; Test 27f: The Dunnett test**; Comparisons between the marginal means; Evaluation of an omnibus hypothesis involving more than two marginal means; Comparisons between specific groups that are a combination of both factors; The computation of a confidence interval for a comparison; Analysis of simple effects)
 2. Evaluation of the homogeneity of variance assumption of the between-subjects factorial analysis of variance
 3. Computation of the power of the between-subjects factorial analysis of variance

4. Measures of magnitude of treatment effect for the between-subjects factorial analysis of variance: **Omega squared (Test 27g)** and **Cohen's f index (Test 27h)**
5. Computation of a confidence interval for the mean of a population represented by a group
6. Additional analysis of variance procedures for factorial designs
- VII. Additional Discussion of the Between-Subjects Factorial Analysis of Variance
 1. Theoretical rationale underlying the between-subjects factorial analysis of variance
 2. Definitional equations for the between-subjects factorial analysis of variance
 3. Unequal sample sizes
 4. Final comments on the between-subjects factorial analysis of variance (Fixed-effects versus random-effects versus mixed-effects models; Nested factors/hierarchical designs and designs involving more than two factors)
- VIII. Additional Examples Illustrating the Use of the Between-Subjects Factorial Analysis of Variance
- IX. Addendum
 1. Discussion of and computational procedures for additional analysis of variance procedures for factorial designs: **Test 27i: The factorial analysis of variance for a mixed design; Test 27j: The within-subjects factorial analysis of variance**

Measures of Association/Correlation

Test 28. The Pearson Product-Moment Correlation Coefficient

- I. Hypothesis Evaluated with Test and Relevant Background Information
- II. Example
- III. Null versus Alternative Hypotheses
- IV. Test Computations
- V. Interpretation of the Test Results (**Test 28a: Test of significance for a Pearson product-moment correlation coefficient**; The coefficient of determination)
- VI. Additional Analytical Procedures for the Pearson Product-Moment Correlation Coefficient and/or Related Tests
 1. Derivation of a regression line
 2. The standard error of estimate
 3. Computation of a confidence interval for the value of the criterion variable
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 5. **Test 28b: Test for evaluating the hypothesis that the true population correlation is a specific value other than zero**
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7. **Test 28c: Test for evaluating a hypothesis on whether there is a significant difference between two independent correlations**
8. **Test 28d: Test for evaluating a hypothesis on whether k independent correlations are homogeneous**
9. **Test 28e: Test for evaluating the null hypothesis $H_0: \rho_{xz} = \rho_{yz}$**
10. Tests for evaluating a hypothesis regarding one or more regression coefficients (**Test 28f: Test for evaluating the null hypothesis $H_0: \beta = 0$** ; Test 28g: Test for evaluating the null hypothesis $H_0: \beta_1 = \beta_2$)
11. Additional correlational procedures
- VII. Additional Discussion of the Pearson Product-Moment Correlation Coefficient
 1. The definitional equation for the Pearson product-moment correlation coefficient
 2. Residuals
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 4. The homoscedasticity assumption of the Pearson product-moment correlation coefficient
 5. The phi coefficient as a special case of the Pearson product-moment correlation coefficient
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- VIII. Additional Examples Illustrating the Use of the Pearson Product-Moment Correlation Coefficient
- IX. Addendum
 1. Bivariate measures of correlation that are related to the Pearson product-moment correlation coefficient (**Test 28h: The point-biserial correlation coefficient** (and **Test 28h-a: Test of significance for a point-biserial correlation coefficient**); **Test 28i: The biserial correlation coefficient** (and **Test 28i-a: Test of significance for a biserial correlation coefficient**); **Test 28j: The tetrachoric correlation coefficient** (and **Test 28j-a: Test of significance for a tetrachoric correlation coefficient**))
 2. Multiple regression analysis (General introduction to multiple regression analysis; Computational procedures for multiple regression analysis involving three variables: **Test 28k: The multiple correlation coefficient**; The coefficient of multiple determination; **Test 28k-a: Test of significance for a multiple correlation coefficient**; The multiple regression equation; The standard error of multiple estimate; Computation of a confidence interval for Y' ; Evaluation of the relative importance of the predictor variables; Evaluating the significance of a regression coefficient; Computation of a confidence interval for a regression coefficient; Partial and semipartial correlation (**Test 28l: The partial correlation coefficient** and **Test 28l-a: Test of significance for a partial correlation coefficient**; **Test 28m: The semipartial**

correlation coefficient and **Test 28m-a: Test of significance for a semipartial correlation coefficient**); Final comments on multiple regression analysis)

3. Additional multivariate procedures involving correlational analysis (Factor analysis; Canonical correlation; Discriminant analysis and logistic regression)
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Test 29. Spearman's Rank-Order Correlation Coefficient

- I. Hypothesis Evaluated with Test and Relevant Background Information
- II. Example
- III. Null versus Alternative Hypotheses
- IV. Test Computations
- V. Interpretation of the Test Results (**Test 29a: Test of significance for Spearman's rank-order correlation coefficient**)
- VI. Additional Analytical Procedures for Spearman's Rank-Order Correlation Coefficient and/or Related Tests
 1. Tie correction for Spearman's rank-order correlation coefficient
 2. Spearman's rank-order correlation coefficient as a special case of the Pearson product-moment correlation coefficient
 3. Regression analysis and Spearman's rank-order correlation coefficient
 4. Partial rank correlation
 5. Use of Fisher's z_r transformation with Spearman's rank-order correlation coefficient
- VII. Additional Discussion of Spearman's Rank-Order Correlation Coefficient
 1. The relationship between Spearman's rank-order correlation coefficient, Kendall's coefficient of concordance, and the Friedman two-way analysis of variance by ranks
 2. Power efficiency of Spearman's rank-order correlation coefficient
 3. Brief discussion of Kendall's tau: An alternative measure of association for two sets of ranks
 4. Weighted rank/top-down correlation
- VIII. Additional Examples Illustrating the Use of the Spearman's Rank-Order Correlation Coefficient

Test 30. Kendall's Tau

- I. Hypothesis Evaluated with Test and Relevant Background Information
- II. Example
- III. Null versus Alternative Hypotheses
- IV. Test Computations
- V. Interpretation of the Test Results (**Test 30a: Test of significance for Kendall's tau**)
- VI. Additional Analytical Procedures for Kendall's Tau and/or Related Tests
 1. Tie correction for Kendall's tau
 2. Regression analysis and Kendall's tau
 3. Partial rank correlation
 4. Sources for computing a confidence interval for Kendall's tau
- VII. Additional Discussion of Kendall's Tau
 1. Power efficiency of Kendall's tau
 2. Kendall's coefficient of agreement
- VIII. Additional Examples Illustrating the Use of Kendall's Tau

Test 31. Kendall's Coefficient of Concordance

- I. Hypothesis Evaluated with Test and Relevant Background Information
- II. Example
- III. Null versus Alternative Hypotheses
- IV. Test Computations
- V. Interpretation of the Test Results (**Test 31a: Test of significance for Kendall's coefficient of concordance**)
- VI. Additional Analytical Procedures for Kendall's Coefficient of Concordance and/or Related Tests
 1. Tie correction for Kendall's coefficient of concordance
- VII. Additional Discussion of Kendall's Coefficient of Concordance
 1. Relationship between Kendall's coefficient of concordance and Spearman's rank-order correlation coefficient
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- VIII. Additional Examples Illustrating the Use of Kendall's Coefficient of Concordance

Test 32. Goodman and Kruskal's Gamma

- I. Hypothesis Evaluated with Test and Relevant Background Information
- II. Example
- III. Null versus Alternative Hypotheses
- IV. Test Computations
- V. Interpretation of the Test Results (**Test 32a: Test of significance for Goodman and Kruskal's gamma**)
- VI. Additional Analytical Procedures for Goodman and Kruskal's Gamma and/or Related Tests
 1. The computation of a confidence interval for the value of Goodman and Kruskal's gamma

2. **Test 32b: Test for evaluating the null hypothesis $H_0: \gamma_1 = \gamma_2$**
 3. Sources for computing a partial correlation coefficient for Goodman and Kruskal's gamma
- VII. Additional Discussion of Goodman and Kruskal's Gamma
1. Relationship between Goodman and Kruskal's gamma and Yule's Q
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- VIII. Additional Examples Illustrating the Use of Goodman and Kruskal's Gamma

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- Table A22. Table of Critical Values for the Lilliefors test for Normality
- Table A23. Table of Critical Values for the Kolmogorov-Smirnov Test for Two Independent Samples

Introduction

Although it is assumed that the reader has prior familiarity with these topics, the intent of this **Introduction** is to provide a general overview of the basic terminology employed within the areas of descriptive statistics and experimental design. It will also review basic concepts that are required for both understanding and using the statistical procedures that are described in this book. Following the **Introduction** is an outline of all the procedures that are covered, as well as decision-making charts to aid the reader in selecting the appropriate statistical procedure.

Descriptive versus Inferential Statistics

Statistics is a field within mathematics that involves the summary and analysis of data. The field of statistics can be divided into two general areas, **descriptive statistics** and **inferential statistics**. **Descriptive statistics** is a branch of statistics in which data are only used for descriptive purposes and are not employed to make predictions. Thus, descriptive statistics consists of methods and procedures for presenting and summarizing data. The procedures most commonly employed in descriptive statistics are the use of tables and graphs, and the computation of measures of central tendency and variability. **Measures of association or correlation**, which are covered in this book, are also categorized by some sources as descriptive statistical procedures, insofar as they serve to describe the relationship between two or more variables.

Inferential statistics employs data in order to draw inferences (i.e., derive conclusions) or make predictions. Typically, in inferential statistics sample data are employed to draw inferences about one or more populations from which the samples have been derived. Whereas a **population** consists of the sum total of subjects or objects that share something in common with one another, a **sample** is a set of subjects or objects which have been derived from a population. For a sample to be useful in drawing inferences about the larger population from which it was drawn, it must be representative of the population. Thus, typically (although there are exceptions) the ideal sample to employ in research is a **random sample**. In a random sample, each subject or object in the population has an equal likelihood of being selected as a member of that sample. In point of fact, it would be highly unusual to find an experiment that employed a truly random sample. Pragmatic and/or ethical factors make it literally impossible in most instances to obtain random samples for research. Insofar as a sample is not random, it will limit the degree to which a researcher will be able to generalize one's results. Put simply, one can only generalize to objects or subjects that are similar to the sample employed.

Statistic versus Parameter

A **statistic** refers to a characteristic of a sample, such as the average score (also known as the **mean**). A **parameter**, on the other hand, refers to a characteristic of a population (such as the average of a whole population). In inferential statistics the computed value of a statistic (e.g., a sample mean) is employed to make inferences about a parameter in the population from which the sample was derived (e.g., the population mean). The statistical procedures described in this book all employ data derived from one or more samples, in order to draw inferences or make predictions with respect to the larger population(s) from which the sample(s) were drawn.

A statistic can be employed for either descriptive or inferential purposes. An example of

using a statistic for descriptive purposes is obtaining the mean of a group (which represents a sample) in order to summarize the average performance of the group. On the other hand, if we use the mean of a group to estimate the mean of a larger population the group is supposed to represent, the statistic (i.e., the group mean) is being employed for inferential purposes. The most basic statistics that are employed for both descriptive and inferential purposes are **measures of central tendency** (of which the mean is an example) and **measures of variability**.

When data from a sample are employed to estimate a population parameter, any statistic derived from the sample should be **unbiased**. An **unbiased statistic** is one that provides the most accurate estimate of a population parameter. A **biased statistic**, on the other hand, does not provide as accurate an estimate of that parameter. The subject of bias in statistics will be discussed later in reference to the **mean** (which is the most commonly employed measure of central tendency), and the **variance** (which is the most commonly employed measure of variability).

Levels of Measurement

Typically, information that is quantified in research for purposes of analysis is categorized with respect to the level of measurement the data represent. Different levels of measurement contain different amounts of information with respect to whatever the data are measuring. Statisticians generally conceptualize data as fitting within one of the following four measurement categories: **nominal data** (also known as **categorical data**), **ordinal data** (also known as **rank-order data**), **interval data**, and **ratio data**. As one moves from the lowest level of measurement, nominal data, to the highest level, ratio data, the amount of information provided by the numbers increases, as well the meaningful mathematical operations that can be performed on those numbers. Each of the levels of measurement will now be discussed in more detail.

a) **Nominal/categorical level measurement** In nominal/categorical measurement, numbers are employed merely to identify mutually exclusive categories, but cannot be manipulated in a meaningful mathematical manner. As an example, a person's social security number represents nominal measurement, since it is used purely for purposes of identification, and cannot be meaningfully manipulated in a mathematical sense (i.e., adding, subtracting, etc. the social security numbers of people does not yield anything of tangible value).

b) **Ordinal/rank-order level measurement** In an ordinal scale, the numbers represent rank-orders, and do not give any information regarding the differences between adjacent ranks. Thus, the order of finish in a horse race represents an ordinal scale. If in a race Horse A beats Horse B in a photo finish, and Horse B beats Horse C by twenty lengths, the respective order of finish of the three horses reveals nothing about the fact that the distance between the first and second place horses was minimal, while the difference between second and third place horses was substantial.

c) **Interval level measurement** An interval scale not only considers the relative order of the measures involved (as is the case with an ordinal scale) but, in addition, is characterized by the fact that throughout the length of the scale, equal differences between measurements correspond to equal differences in the amount of the attribute being measured. What this translates to is that if IQ is conceptualized as an interval scale, the one point difference between a person who has an IQ of 100 and someone who has an IQ of 101 should be equivalent to the one point difference between a person who has an IQ of 140 and someone with an IQ of 141. In actuality some psychologists might argue this point, suggesting that a greater increase in intelligence is required to jump from an IQ of 140 to 141, than to jump from an IQ of 100 to 101. In fact, if the latter is true, a one point difference does not reflect the same magnitude of difference across the full range of the IQ scale. Although in practice IQ and most other human characteristics measured by psychological tests (such as anxiety, introversion–extroversion, etc.) are treated as interval

scales, many researchers would argue that they are more appropriately categorized as ordinal scales. Such an argument would be based on the fact that such measures do not really meet the requirements of an interval scale, because it cannot be demonstrated that equal numerical differences at different points of the scale are comparable.

It should also be noted that, unlike ratio scales which will be discussed next, interval scales do not have a true zero point. If interval scales have a zero score that can be assigned to a person or object, it is assumed to be arbitrary. Thus, in the case of IQ we can ask the question of whether or not there is truly an IQ which is so low that it literally represents zero IQ. In reality, you probably can only say a person who is dead has a zero IQ! In point of fact, someone who has obtained an IQ of zero on an IQ test has been assigned that score because his performance on the test was extremely poor. The zero IQ designation does not necessarily mean the person could not answer any of the test questions (or, to go further, that the individual possesses none of the requisite skills or knowledge for intelligence). The developers of the test just decided to select a certain minimum score on the test and designate it as the zero IQ point.

d) **Ratio level measurement** As is the case with interval level measurement, ratio level measurement is also characterized by the fact that throughout the length of the scale, equal differences between measurements correspond to equal differences in the amount of the attribute being measured. However, ratio level measurement is also characterized by the fact that it has a true zero point. Because of the latter, with ratio measurement one is able to make meaningful ratio statements with regard to the attribute/variable being measured. To illustrate these points, most physical measures such as weight, height, blood glucose level, as well as measures of certain behaviors such as the number of times a person coughs or the number of times a child cries, represent ratio scales. For all of the aforementioned measures there is a true zero point (i.e., zero weight, zero height, zero blood glucose, zero coughs, zero episodes of crying), and for each of these measures one is able to make meaningful ratio statements (such as Ann weighs twice as much as Joan, Bill is one-half the height of Steve, Phil's blood glucose is 100 times Sam's, Mary coughs five times as often as Pete, and Billy cries three times as much as Heather).

Continuous versus Discrete Variables

When measures are obtained on people or objects, in most instances we assume that there will be variability. Since we assume variability, if we are quantifying whatever it is that is being measured, not everyone or everything will produce the same score. For this reason, when something is measured it is commonly referred to as a **variable**. As noted above, variables can be categorized with respect to the level of measurement they represent. In addition, a variable can be categorized with respect to whether it is **continuous** or **discrete**. A **continuous variable** can assume any value within the range of scores that define the limits of that variable. A **discrete variable**, on the other hand, can assume only a limited number of values. To illustrate, temperature (which can assume both integer and fractional/decimal values within a given range) is a **continuous variable**. Theoretically there are an infinite number of possible temperature values, and the number of temperature values we can measure is limited only by the precision of the instrument we are employing to obtain the measurements. The face value of a die, on the other hand, is a **discrete variable**, since it can only assume the integer values 1 through 6.

Measures of Central Tendency

Earlier in the **Introduction** it is noted that the most commonly employed statistics are measures of central tendency and measures of variability. This section will describe three measures of central tendency: the **mode**, the **median**, and the **mean**.

The mode The **mode** is the most frequently occurring score in a distribution of scores. A mode that is derived for a sample is a statistic, whereas the mode of a population is a parameter. In the following distribution of scores the mode is 5, since it occurs two times, whereas all other scores occur only once: 0, 1, 2, 5, 5, 8, 10. If more than one score occurs with the highest frequency, it is possible to have two or more modes in a distribution. Thus, in the distribution 0, 1, 2, 5, 6, 8, 10, all of the scores represent the mode, since each score occurs one time. A distribution with more than one mode is referred to as a **multimodal distribution**. If it happens that two scores both occur with the highest frequency, the distribution would be described as a **bimodal** distribution, which represents one type of multimodal distribution. The distribution 0, 5, 5, 8, 9, 9, 12 is bimodal, since the scores 5 and 9 both occur two times, and all other scores appear once.

The most common situation in which the mode is employed as a descriptive measure is when a large body of data is presented in a tabular format listing the frequency of each score. Such a table is referred to as a **frequency distribution**. An example of a frequency distribution would be if the scores 0, 5, 5, 8, 9, 9, 12 were arranged in a tabular format. Specifically, each score in the range 0 to 12 would be recorded in one column, and an adjacent column would list the frequency of occurrence for each score. An example of a frequency distribution are the first two columns of [Table 7.1](#) in Section I of the **Kolmogorov–Smirnov goodness-of-fit test for a single sample (Test 7)**. The latter table also contains a **cumulative frequency distribution** (which is represented by the third column of the table). In a **cumulative frequency distribution**, the frequency recorded for each score represents the frequency of a score plus the frequencies of all scores which are less than that score. Scores are arranged ordinally, with the lowest score at the bottom of the distribution, and the highest score at the top of the distribution. The cumulative frequency for the lowest score will simply be the frequency for that score, since there are no scores below it. On the other hand, the cumulative frequency for the highest score will always equal n , the total number of scores in the distribution.

The median The **median** is the middle score in a distribution. If there is an odd number of scores in a distribution, in order to determine the median the following protocol should be employed: Divide the total number of scores by 2 and add .5 to the result of the division. The obtained value indicates the **ordinal position** of the score which represents the median of the distribution (note that this value does not represent the median). Thus, if we have a distribution consisting of five scores (e.g., 6, 8, 9, 13, 16), we divide the number of scores in the distribution by two, and add .5 to the result of the division. Thus, $(5/2) + .5 = 3$. The obtained value of 3 indicates that if the five scores are arranged ordinally (i.e., from lowest to highest), the median is the 3rd highest (or 3rd lowest) score in the distribution. With respect to the distribution 6, 8, 9, 13, 16, the value of the median will equal 9, since 9 is the score in the third ordinal position.

If there are an even number of scores in a distribution, there will be two middle scores. The median is the average of the two middle scores. To determine the ordinal positions of the two middle scores, divide the total number of scores in the distribution by 2. The number value obtained by that division and the number value that is one above it represent the ordinal positions of the two middle scores. To illustrate, assume we have a distribution consisting of the following six scores: 6, 8, 9, 12, 13, 16. To determine the median, we initially divide 6 by 2 which equals 3. Thus, if we arrange the scores ordinally, the 3rd and 4th (since $3 + 1 = 4$) scores are the middle scores. The average of these scores, which are, respectively, 9 and 12, is the median (which will be represented by the notation M). Thus, $M = (9 + 12)/2 = 10.5$. Note once again that in this example, as was the case in the previous one, the initial values computed (3 and 4) do not themselves represent the median, but instead represent the ordinal position of the scores used to compute the median. As was the case with the mode, a median value derived for a sample is a statistic, whereas the median of a whole population is a parameter.

The mean The **mean**, which is the most commonly employed measure of central tendency, is the average score in a distribution. Within the framework of the discussion to follow, the notation n will represent the number of subjects or objects in a sample, and the notation N will represent the total number of subjects or objects in the population from which the sample is derived.

Equation I.1 is employed to compute the mean of a sample. Σ , which is the upper case Greek letter **sigma**, is a summation sign. The notation ΣX indicates that the set of scores should be summed.

$$\bar{X} = \frac{\Sigma X}{n} \quad \text{(Equation I.1)}$$

Sometimes Equation I.1 is written in the following more complex but equivalent form containing subscripts: $\bar{X} = \Sigma_{i=1}^n X_i / n$. In the latter equation, the notation $\Sigma_{i=1}^n X_i$ indicates that beginning with the first score, scores 1 through n (i.e., all the scores) are to be summed. X_i represents the score of the i^{th} subject or object.

Equation I.1 will now be applied to the following distribution of five scores: 6, 8, 9, 13, 16. Since $n = 5$ and $\Sigma X = 52$, $\bar{X} = \Sigma X / n = 52 / 5 = 10.4$.

Whereas Equation I.1 describes how one can compute the mean of a sample, Equation I.2 describes how one can compute the mean of a population. The simplified version without subscripts is to the right of the first = sign, and the subscripted version of the equation is to the right of the second = sign. The mean of a population is represented by the notation μ , which is the lower case Greek letter **mu**. In practice, it would be highly unusual to have occasion to compute the mean of a population. Indeed, a great deal of analysis in inferential statistics is concerned with trying to estimate the mean of a population from the mean of a sample.

$$\mu = \frac{\Sigma X}{N} = \frac{\sum_{i=1}^N X}{N} \quad \text{(Equation I.2)}$$

Note that in the numerator of Equation I.2 all N scores in the population are summed, as opposed to just summing n scores when the value of \bar{X} is computed. The sample mean \bar{X} is an **unbiased estimate** of the population mean μ , which indicates that if one has a distribution of n scores, \bar{X} provides the best possible estimate of the true value of μ . Typically, when the mean is used as a measure of central tendency, it is employed with interval or ratio level data.

Measures of Variability

In this section a number of measures of variability will be discussed. Primary emphasis, however, will be given to the **standard deviation** and the **variance**, which are the most commonly employed measures of variability.

a) **The range** The **range** is the difference between the highest and lowest score in a distribution. Thus in the distribution 2, 3, 5, 6, 7, 12, the range is the difference between 12 (the highest score) and 2 (the lowest score). Thus: Range = $12 - 2 = 10$. Some sources add one to the obtained value, and would thus say that the Range = 11. Although the **range** is employed on occasion for descriptive purposes, it is of little use in inferential statistics.

b) **Quantiles, percentiles, quartiles, and deciles** A **quantile** is a measure that divides a distribution into equidistant percentage points. Examples of quantiles are **percentiles**, **quartiles**, and **deciles**. **Percentiles** divide a distribution into blocks comprised of one percentage point (or blocks that comprise a proportion equal to .01 of the distribution). A specific percentile value

corresponds to the point in a distribution at which a given percentage of scores falls at or below. Thus, if an IQ test score of 115 falls at the 84th percentile, it means 84% of the population has an IQ of 115 or less. The term **percentile rank** is also employed to mean the same thing as a percentile — in other words, we can say that an IQ score of 115 has a percentile rank of 84%.

Deciles divide a distribution into blocks comprised of ten percentage points (or blocks that comprise a proportion equal to .10 of the distribution). A distribution can be divided into ten deciles, the upper limits of which are defined by the 10th percentile, 20th percentile, ..., 90th percentile, and 100th percentile. Thus, a score that corresponds to the 10th percentile falls at the upper limit of the first decile of the distribution. A score that corresponds to the 20th percentile falls at the upper limit of the second decile of the distribution, and so on. The **interdecile range** is the difference between the scores at the 90th percentile (the upper limit of the ninth decile) and the 10th percentile.

Quartiles divide a distribution into blocks comprised of 25 percentage points (or blocks that comprise a proportion equal to .25 of the distribution). A distribution can be divided into four **quartiles**, the upper limits of which are defined by the 25th percentile, 50th percentile (which corresponds to the median of the distribution), 75th percentile, and 100th percentile. Thus, a score that corresponds to the 25th percentile falls at the upper limit of the first quartile of the distribution. A score that corresponds to the 50th percentile falls at the upper limit of the second quartile of the distribution, and so on. The **interquartile range** is the difference between the scores at the 75th percentile (which is the upper limit of the third quartile) and the 25th percentile.

Infrequently, the interdecile or interquartile ranges may be employed to represent variability. An example of a situation where a researcher might elect to employ either of these measures to represent variability would be when the researcher wishes to omit a few extreme scores in a distribution. Such extreme scores are referred to as **outliers**. Specifically, an **outlier** is a score in a set of data which is so extreme that, by all appearances, it is not representative of the population from which the sample is ostensibly derived. Since the presence of outliers can dramatically affect variability (as well as the value of the sample mean), their presence may lead a researcher to believe that the variability of a distribution might best be expressed through use of the interdecile or interquartile range (as well as the fact that when outliers are present, the sample median is more likely than the mean to be a representative measure of central tendency). Outliers are discussed in detail in Section VI of the **t test for two independent samples (Test 11)**.

c) **The variance and the standard deviation** The most commonly employed measures of variability in both inferential and descriptive statistics are the **variance** and the **standard deviation**. These two measures are directly related to one another, since the standard deviation is the square root of the variance (and thus the variance is the square of the standard deviation). As is the case with the mean, the standard deviation and the variance are generally only employed with interval or ratio level data.

The formal definition of the variance is that it is the mean of the squared difference scores (which are also referred to as **deviation scores**). This definition implies that in order to compute the variance of a distribution one must subtract the mean of the distribution from each score, square each of the difference scores, sum the squared difference scores, and divide the latter value by the number of scores in the distribution. The logic of this definition is reflected in the **definitional equations** which will be presented later in this section for both the variance and the standard deviation.

A **definitional equation** for a statistic (or parameter) contains the specific mathematical operations that are described in the definition of that statistic (or parameter). On the other hand, a **computational equation** for the same statistic (or parameter) does not clearly reflect the definition of that statistic (or parameter). A computational equation, however, facilitates computation

of the statistic (or parameter), since it is computationally less involved than the definitional equation. In this book, in instances where a definitional and computational equation are available for computing a test statistic, the computational equation will generally be employed to facilitate calculations.

The following notation will be used in the book with respect to the values of the variance and the standard deviation.

σ^2 (where σ is the lower case Greek letter **sigma**) will represent the **variance of a population**.

s^2 will represent the variance of a sample, when the variance is employed for descriptive purposes. s^2 will be a **biased estimate of the population variance** σ^2 and, because of this, s^2 will generally underestimate the true value of σ^2 .

\tilde{s}^2 will represent the variance of a sample, when the variance is employed for inferential purposes. \tilde{s}^2 will be an **unbiased estimate of the population variance** σ^2 .

σ will represent the **standard deviation of a population**.

s will represent the standard deviation of a sample, when the standard deviation is employed for descriptive purposes. s will be a **biased estimate of the population standard deviation** σ and, because of this, s will generally underestimate the true value of σ .

\tilde{s} will represent the standard deviation of a sample, when the standard deviation is employed for inferential purposes. \tilde{s} will be an **unbiased estimate of the population standard deviation** σ .¹

Equations I.3–I.8 are employed to compute the values σ^2 , s^2 , \tilde{s}^2 , σ , s , and \tilde{s} . Note that in each case, two equivalent methods are presented for computing the statistic or parameter in question. The formula to the left is the definitional equation, whereas the formula to the right is the computational equation.

$$\sigma^2 = \frac{\sum(X - \mu)^2}{N} = \frac{\sum X^2 - \frac{(\sum X)^2}{N}}{N} \quad \text{(Equation I.3)}$$

$$s^2 = \frac{\sum(X - \bar{X})^2}{n} = \frac{\sum X^2 - \frac{(\sum X)^2}{n}}{n} \quad \text{(Equation I.4)}$$

$$\tilde{s}^2 = \frac{\sum(X - \bar{X})^2}{n - 1} = \frac{\sum X^2 - \frac{(\sum X)^2}{n}}{n - 1} \quad \text{(Equation I.5)}$$

$$\sigma = \sqrt{\frac{\sum(X - \mu)^2}{N}} = \sqrt{\frac{\sum X^2 - \frac{(\sum X)^2}{N}}{N}} \quad \text{(Equation I.6)}$$

$$s = \sqrt{\frac{\sum(X - \bar{X})^2}{n}} = \sqrt{\frac{\sum X^2 - \frac{(\sum X)^2}{n}}{n}} \quad \text{(Equation I.7)}$$

$$\tilde{s} = \sqrt{\frac{\sum(X - \bar{X})^2}{n - 1}} = \sqrt{\frac{\sum X^2 - \frac{(\sum X)^2}{n}}{n - 1}} \quad \text{(Equation I.8)}$$

When the variance or standard deviation of a sample is computed within the framework of an inferential statistical test, one always wants an unbiased estimate of the population variance or the population standard deviation. Thus, the computational form of Equation I.5 will be employed throughout this book when a sample variance is used to estimate a population variance, and the computational form of Equation I.8 will be employed when a sample standard deviation is used to estimate a population standard deviation.

The reader should take note of the fact that some sources employ subscripted versions of the above equations. Thus, the computational form of Equation I.5 is often written as:

$$\tilde{s}^2 = \frac{\sum_{i=1}^n X_i^2 - \frac{\left(\sum_{i=1}^n X_i\right)^2}{n}}{n - 1}$$

Although the subscripted version will not be employed for computing the values of \tilde{s}^2 and \tilde{s} , in the case of some equations that are presented, subscripted versions may be employed in order to clarify the mathematical operations involved in computing a statistic.

As noted previously, for the same set of data the value of \tilde{s}^2 will always be larger than the value of s^2 . This can be illustrated with a distribution consisting of the five scores: 6, 8, 9, 13, 16. The following values are substituted in Equations I.4 and I.5: $\sum X = 52$, $\sum X^2 = 606$, $n = 5$.

$$s^2 = \frac{606 - \frac{(52)^2}{5}}{5} = 13.04$$

$$\tilde{s}^2 = \frac{606 - \frac{(52)^2}{5}}{5 - 1} = 16.3$$

Since the standard deviation is the square root of the variance, we can quickly determine that $s = \sqrt{s^2} = \sqrt{13.04} = 3.61$ and $\tilde{s} = \sqrt{\tilde{s}^2} = \sqrt{16.3} = 4.04$. Note that $\tilde{s}^2 > s^2$ and $\tilde{s} > s$.

Table I.1 summarizes the computation of the unbiased estimate of the population variance (\tilde{s}^2), employing both the definitional and computational equations. Note that in the two versions for computing \tilde{s}^2 listed for Equation I.5, the numerator values $\sum X^2 - [(\sum X)^2/n]$ and $\sum (X - \bar{X})^2$ are equivalent. Thus, in **Table I.1**, the sum of the values of the last column $\sum (X - \bar{X})^2 = 65.20$, equals $\sum X^2 - [(\sum X)^2/n] = 606 - [(52)^2/5] = 65.20$.

The reader should take note of the following with respect to the standard deviation and the variance:

a) The value of a standard deviation or a variance can never be a negative number. If a negative number is ever obtained for either value, it indicates a mistake has been made in the calculations. The only time the value of a standard deviation or variance will not be a positive number is when its value equals zero. The only instance in which the value of both the standard deviation and variance of a distribution will equal zero is when all of the scores in the distribution are identical to one another.

b) As the value of the sample size (n) increases, the difference between the values of s^2 and \tilde{s}^2 will decrease. In the same respect, as the value of n increases, the difference between the values of s and \tilde{s} will decrease. Thus, the biased estimate of the variance (or standard deviation) will be more likely to underestimate the true value of the population variance (or standard deviation) with small sample sizes than it will with large sample sizes.

Table I.1 Computation of Estimated Population Variance

X	X^2	\bar{X}	$(X - \bar{X})$	$(X - \bar{X})^2$
6	36	10.4	$(6 - 10.4) = -4.4$	$(-4.4)^2 = 19.36$
8	64	10.4	$(8 - 10.4) = -2.4$	$(-2.4)^2 = 5.76$
9	81	10.4	$(9 - 10.4) = -1.4$	$(-1.4)^2 = 1.96$
13	169	10.4	$(13 - 10.4) = 2.6$	$(2.6)^2 = 6.76$
16	256	10.4	$(16 - 10.4) = 5.6$	$(5.6)^2 = 31.36$
$\Sigma X = 52$	$\Sigma X^2 = 606$		$\Sigma(X - \bar{X}) = 0$	$\Sigma(X - \bar{X})^2 = 65.20$

$$\tilde{s}^2 = \frac{\Sigma X^2 - \frac{(\Sigma X)^2}{n}}{n - 1} = \frac{606 - \frac{(52)^2}{5}}{5 - 1} = \frac{65.20}{5 - 1} = 16.3$$

$$\tilde{s}^2 = \frac{\Sigma(X - \bar{X})^2}{n - 1} = \frac{65.20}{5 - 1} = 16.3$$

c) The numerator of any of the equations employed to compute a variance or a standard deviation is often referred to as the **sum of squares**. Thus in the example in this section, the value of the sum of squares is 65.2, since $\Sigma X^2 - [(\Sigma X)^2/n] = 606 - [(52)^2/5] = 65.2$. The denominators of both Equation I.5 and Equation I.8 are often referred to as the **degrees of freedom** (a concept that is discussed later in the book within the framework of the **single-sample *t* test (Test 2)**). Based on what has been said with respect to the sum of squares and the degrees of freedom, the variance is sometimes defined as the sum of squares divided by the degrees of freedom.

d) **The coefficient of variation** An alternative, although infrequently employed measure of variability, is the **coefficient of variation**. Since the values of the standard deviation and variance are a direct function of the magnitude of the scores in a sample/population, it can sometimes be useful to express variability in reference to the size of the mean of a distribution. By doing the latter, one can compare the values of the standard deviations and variances of distributions that have dramatically different mean values and/or employ different units of measurement. The coefficient of variation (represented by the notation CV) allows one to do this. The coefficient of variation is computed with Equation I.9.

$$CV = \frac{\tilde{s}}{\bar{X}} \quad \text{(Equation I.9)}$$

The following should be noted with respect to Equation I.9: a) When the values of σ and μ are known, they can be employed in place of \tilde{s} and \bar{X} ; and b) Sometimes the value computed for CV is multiplied by 100 in order to express it as a percentage.

Note that the coefficient of variation is nothing more than a ratio of the value of the standard deviation relative to the value of the mean. The larger the value of CV computed for a variable, the greater the degree of variability there is on that variable. Unlike the standard deviation and variance, the numerical value represented by CV is not in the units that are employed to measure the variable for which it is computed.

To illustrate the latter, let us assume that we wish to compare the variability of income between two countries that employ dramatically different values of currency. The mean monthly income in **Country A** is $\bar{X}_A = 40$ jaspars, with a standard deviation of $\tilde{s}_A = 10$ jaspars. The

mean monthly income in **Country B** is $\bar{X}_B = 2000$ rocs, with a standard deviation of $\tilde{s}_B = 100$ rocs. Note that the mean and standard deviation for each country is expressed in the unit of currency employed in that country. When we employ Equation I.9, we compute that the coefficient of variations for the two countries are $CV_A = 10/40 = .25$ and $CV_B = 100/2000 = .05$. The latter CV values are just simple ratios, and are not numbers based on the scale for the unit of currency employed in a given country. In other words, $CV_A = .25$ is not .25 jaspars, but is simply the ratio .25. In the same respect $CV_B = .05$ is not .05 rocs, but is simply the ratio .05. Consequently, by dividing the larger value $CV_A = .25$ by the smaller value $CV_B = .05$ we can determine that there is five times more variability in income in **Country A** than there is in **Country B** (i.e., $CV_A / CV_B = .25 / .05 = 5$). If we express our result as a percentage, we can say that there is $5 \times 100\% = 500\%$ more variability in income in **Country A** than there is in **Country B**. If, on the other hand, we had divided $\tilde{s}_B = 100$ rocs by $\tilde{s}_A = 10$ jaspars (i.e., $\tilde{s}_B / \tilde{s}_A = 100 / 10 = 10$), we would have erroneously concluded that there is ten times (or $10 \times 100 = 1000\%$) more variability in income in **Country B** than in **Country A**. The reason why the latter method results in a misleading conclusion is that, unlike the coefficient of variation, it fails to take into account the different units of currency employed in the two countries.

Measures of Skewness and Kurtosis

In addition to the mean and variance, there are two other measures that can provide useful descriptive information about a distribution. These two measures, **skewness** and **kurtosis**, represent the **third** and **fourth moments** of a distribution. The word **moment** is employed to represent to the sum of the deviations from the mean in reference to sample size. Equations I.10 and I.11 respectively represent the general equation for a moment. In Equation I.10, v_i (where v represents the lower case Greek letter **nu**) represents the population parameter for the i^{th} moment about the mean, whereas in Equation I.11, m_i represents the sample statistic for the i^{th} moment about the mean.

$$v_i = \frac{(X - \mu)^r}{N} \quad (\text{Equation I.10})$$

$$m_i = \frac{(X - \bar{x})^r}{n} \quad (\text{Equation I.11})$$

With respect to a sample, the **first moment about the mean** (m_1) is represented by Equation I.12. The **second moment about the mean** (m_2 , which is the sample variance) is represented by Equation I.13. The **third moment about the mean** (m_3 , which as noted above represents skewness, and is also referred to as **symmetry**) is represented by Equation I.14. The **fourth moment about the mean** (m_4 , which as noted above represents kurtosis) is represented by Equation I.15.

$$m_1 = \frac{\Sigma(X - \bar{X})}{n} = 0 \quad (\text{Equation I.12})$$

$$m_2 = \frac{\Sigma(X - \bar{X})^2}{n} \quad (\text{Equation I.13})$$

$$m_3 = \frac{\Sigma(X - \bar{X})^3}{n} \quad (\text{Equation I.14})$$

$$m_4 = \frac{\Sigma(X - \bar{X})^4}{n} \quad (\text{Equation I.15})$$

Although skewness and kurtosis are not employed for descriptive purposes as frequently as the mean and variance, they can provide useful information. Skewness and kurtosis are sometimes employed within the context of determining the **goodness-of-fit** of data in reference to a specific type of distribution — most commonly the normal distribution. Tests of goodness-of-fit are discussed under the **single-sample test for evaluating population skewness (Test 4)**, the **single-sample test for evaluating population kurtosis (Test 5)**, the **Kolmogorov–Smirnov goodness-of-fit test for a single sample (Test 7)** and the **chi-square goodness-of-fit test (Test 8)**.

Skewness Skewness is a measure reflecting the degree to which a distribution is asymmetrical. A symmetrical distribution will result in two identical mirror images when it is split down the middle. The bell shaped or **normal distribution**, which will be discussed in the next section, is the best known example of a symmetrical distribution. When a distribution is not symmetrical, a disproportionate number of scores will fall either to the left or right of the middle of the distribution. [Figure I.1](#) depicts three frequency distributions, only one of which, **Distribution A**, is symmetrical. **Distributions B** and **C** are asymmetrical.

At this point in the discussion it will be useful to review some basic material concerning frequency distributions. As noted above, [Figure I.1](#) depicts a graph of each of three frequency distributions — specifically that of the symmetrical bell-shaped distribution and two skewed distributions. Note that a graph of a frequency distribution is comprised of two axes, a horizontal axis and a vertical axis. The *X*-axis or horizontal axis (which is often referred to as the **abscissa**) is employed to record the range of possible scores on a variable. The *Y*-axis or vertical axis (which is often referred to as the **ordinate**) is employed to represent the frequency (*f*) with which each of the scores noted on the *X*-axis occurs in the population or sample. Graphs of frequency distributions that are comprised of a single line/curve, such as the distributions in [Figure I.1](#), are often referred to as **frequency polygons**. A frequency polygon, which is a series of lines connecting the different points in the distribution, is generally the end result of plotting a frequency distribution for a sample. When all the lines connecting the points are “smoothed over,” the resulting frequency distribution assumes the appearance of the distributions depicted in [Figure I.1](#). A **theoretical frequency distribution** (or as it is sometimes called, a **theoretical probability distribution**), which any of the distributions in [Figure I.1](#) could represent, is a graph of the frequencies for a population distribution. The *X*-axis represents the range of possible scores on a variable in the population, while the *Y*-axis represents the frequency with which each of the scores occurs (or sometimes the proportion/probability of occurrence for the scores is recorded on the *Y*-axis — thus the use of the term **theoretical probability distribution**).

Before discussing the frequency distributions depicted in [Figure I.1](#) in greater detail, it should be noted that there are various other methods which are employed for graphing data. Although these methods will not be discussed in this book (graphical methods are discussed in detail in most introductory books dealing with statistics), it is worth mentioning that it is generally a good idea for a researcher to obtain a plot (i.e., graph) of one’s data prior to evaluating it. The reason for the latter is that a body of data may have certain characteristics which may be important in determining the most appropriate method of analysis. Often such characteristics will not be apparent to a researcher purely on the basis of cursory visual inspection — especially if the researcher is a novice or if there is a large amount of data.

Returning to [Figure I.1](#), **Distribution A** is a **unimodal symmetrical distribution**. Although it is possible to have a symmetrical distribution that is multimodal (i.e., a distribution that has more than one mode), within the framework of the discussion to follow it will be assumed that all

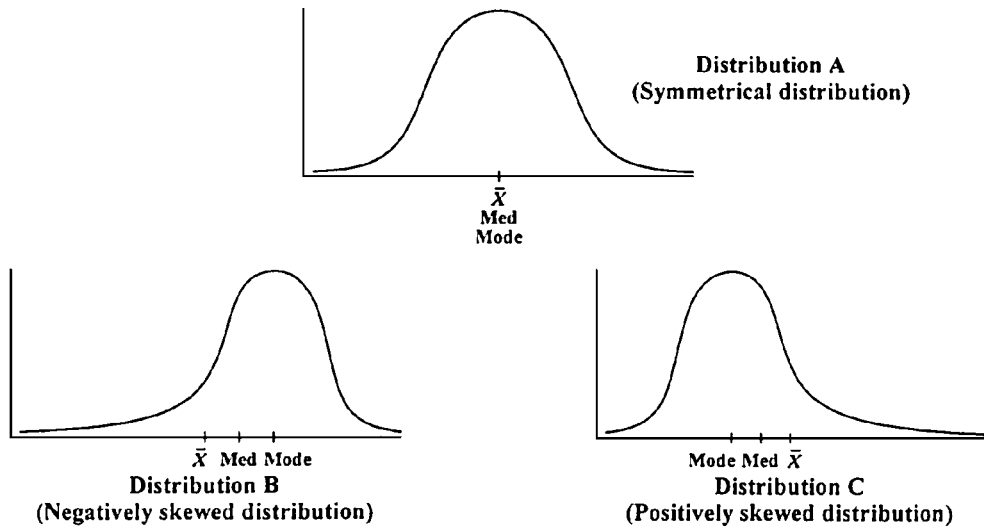


Figure I.1 Symmetrical and Asymmetrical Distributions

of the distributions discussed are unimodal. Note that the number of scores in the left and right tail of **Distribution A** are identical. The **tail** of a distribution refers to the upper/right and lower/left extremes of the distribution. When one tail is heavier than another tail it means that a greater proportion of the scores fall in that tail. In **Distribution A** the two tails are equally weighted.

Turning to the other two distributions, we can state that **Distribution B** is **negatively skewed** (or as it is sometimes called, **skewed to the left**) while **Distribution C** is **positively skewed** (or as it is sometimes called, **skewed to the right**). Note that in **Distribution B** the bulk of the scores fall in the right end of the distribution. This is the case, since the “hump” or upper part of the distribution falls to the right. The tail or lower end of the distribution is on the left side (thus the term **skewed to the left**). **Distribution C**, on the other hand, is **positively skewed**, since the bulk of the scores fall in the left end of the distribution. This is the case, since the “hump” or upper part of the distribution falls to the left. The tail or lower end of the distribution is on the right (thus the term **skewed to the right**). It should be pointed out that **Distributions B** and **C** represent extreme examples of skewed distributions. Thus, distributions can be characterized by skewness, yet not have the imbalance between the left and right tails/extremes that is depicted for **Distributions B** and **C**.

As a general rule, based on whether a distribution is symmetrical, skewed negatively, or skewed positively, one can make a determination with respect to the relative magnitude of the three measures of central tendency discussed earlier in the **Introduction**. In a perfectly symmetrical unimodal distribution the mean, median, and mode will always be the same value. In a skewed distribution the mean, median, and mode will not be the same value. Typically (although there are exceptions), in a negatively skewed distribution, the mean is the lowest value followed by the median and then the mode, which is the highest value. The reverse is the case in a positively skewed distribution, where the mean is the highest value followed by the median, with the mode being the lowest value. The easiest way to remember the arrangement of the three measures of central tendency in a skewed distribution is that they are arranged alphabetically moving in from the tail of the distribution to the highest point in the distribution.

Since a measure of central tendency is supposed to reflect the most representative score for the distribution (although the word “tendency” implies that it may not be limited to a single value), the specific measure of central tendency that is employed for descriptive or inferential

purposes should be a function of the shape of a distribution. In the case of a unimodal distribution that is perfectly symmetrical, the mean (which will always be the same value as the median and mode) will be the best measure of central tendency to use, since it employs the most information. When a distribution is skewed, it is often preferable to employ the median as the measure of central tendency in lieu of the mean. Other circumstances where it may be more desirable to employ the median rather than the mean as a measure of central tendency are discussed in Section VI of the ***t* test for two independent samples** under the discussion of **outliers and data transformation**.

A simple method of estimating skewness for a sample is to compute the value sk , which represents the **Pearsonian coefficient of skewness** (developed in the 1890s by the English statistician Karl Pearson). Equation I.16 is employed to compute the value of sk , which is computed to be $sk = 1.04$ for the distribution summarized in [Table I.1](#). The notation M in Equation I.16 represents the median of the sample.

$$sk = \frac{3(\bar{X} - M)}{\tilde{s}} = \frac{3(10.4 - 9)}{4.04} = 1.04 \quad \text{(Equation I.16)}$$

The value of sk will fall within the range -3 to $+3$, with a value of 0 associated with a perfectly symmetrical distribution. Note that when $\bar{X} > M$, sk will be a positive value, and the larger the value of sk , the greater the degree of positive skew. When $\bar{X} < M$, sk will be a negative value, and the larger the **absolute value**³ of sk , the greater the degree of negative skew. Note that when $\bar{X} = M$, which will be true if a distribution is symmetrical, $sk = 0$.⁴

To illustrate the above, consider the following three distributions **A**, **B**, and **C**, each of which is comprised of 10 scores. **Distribution A** is symmetrical, **Distribution B** is negatively skewed, and **Distribution C** is positively skewed. The value of sk is computed for each distribution.

1) **Distribution A:** 0, 0, 0, 5, 5, 5, 5, 10, 10, 10

The following sample statistics can be computed for **Distribution A**: $\bar{X}_A = 5$; $M_A = 5$; $\tilde{s}_A = 4.08$; $sk_A = [3(5 - 5)]/4.08 = 0$. The value $sk_A = 0$ indicates that **Distribution A** is **symmetrical**. Consistent with the fact that it is symmetrical is that the values of the mean and median are equal. In addition, since the scores are distributed evenly throughout the distribution, both tails/extremes are identical in appearance.

2) **Distribution B:** 0, 1, 1, 9, 9, 10, 10, 10, 10, 10

The following sample statistics can be computed for **Distribution B**: $\bar{X}_B = 7$; $M_B = 9.5$; $\tilde{s}_B = 4.40$; $sk_B = [3(7 - 9.5)]/4.40 = -1.70$. The negative value $sk_B = -1.70$ indicates that **Distribution B** is **negatively skewed**. Consistent with the fact that it is negatively skewed is that the value of the mean is less than the value of the median. In addition, the majority of the scores (i.e., the hump) fall in the right/upper end of the distribution. The lower end of the distribution is the tail on the left side.

3) **Distribution C:** 0, 0, 0, 0, 0, 1, 1, 9, 9, 10

The following sample statistics can be computed for **Distribution C**: $\bar{X}_C = 3$; $M_C = .5$; $\tilde{s}_C = 4.40$; $sk_C = [3(3 - .5)]/4.40 = 1.70$. The positive value $sk_C = 1.70$ indicates that **Distribution C** is **positively skewed**. Consistent with the fact that it is positively skewed is that

the value of the mean is greater than the value of the median. In addition, the majority of the scores (i.e., the hump) fall in the left/lower end of the distribution. The upper end of the distribution is the tail on the right side.

The most precise measure of skewness employs the exact value of the third moment about the mean, designated earlier as m_3 . Cohen (1996) and Zar (1999) note that the unbiased estimate of the population parameter estimated by m_3 can be computed with either Equation I.17 (which is the definitional equation) or Equation I.18 (which is a computational equation).

$$m_3 = \frac{n\sum(X - \bar{X})^3}{(n - 1)(n - 2)} \quad (\text{Equation I.17})$$

$$m_3 = \frac{n\sum X^3 - 3\sum X \sum X^2 + \frac{2(\sum X)^3}{n}}{(n - 1)(n - 2)} \quad (\text{Equation I.18})$$

Note that in Equation I.17, the notation $\sum(X - \bar{X})^3$ indicates that the mean is subtracted from each of the n scores in the distribution, each difference score is cubed, and the n cubed difference scores are summed. The notation $\sum X^3$ in Equation I.18 indicates each of the n scores is cubed, and the n cubed scores are summed. The notation $(\sum X)^3$ in Equation I.18 indicates that the n scores are summed, and the resulting value is cubed. Note that the minimum sample size required to compute skewness is $n = 3$, since any lower value will result in a zero in the denominators of Equations I.17 and I.18, rendering them insoluble.

Since the value computed for m_3 is in cubed units, the unitless statistic g_1 , which is an estimate of the population parameter γ_1 (where γ represents the lower case Greek letter **gamma**), is commonly employed to express skewness. The value of g_1 is computed with Equation I.19.

$$g_1 = \frac{m_3}{\bar{s}^3} \quad (\text{Equation I.19})$$

When a distribution is symmetrical (about the mean), the value of g_1 will equal 0. When the value of g_1 is significantly above 0, a distribution will be positively skewed, and when it is significantly below 0, a distribution will be negatively skewed. Although the normal distribution is symmetrical (with $g_1 = 0$), as noted earlier, not all symmetrical distributions are normal. Examples of nonnormal distributions that are symmetrical are the t distribution and the binomial distribution, when $\pi_1 = .5$ (the meaning of the notation $\pi_1 = .5$ is explained in Section I of the **binomial sign test for a single sample (Test 9)**).

Zar (1999) notes that a population parameter designated $\sqrt{\beta_1}$ (where β represents the lower case Greek letter **beta**) is employed by some sources (e.g., D'Agostino (1970, 1986) and D'Agostino *et al.* (1990)) to represent skewness. Equation I.20 is used to compute $\sqrt{b_1}$, which is the sample statistic employed to estimate the value of $\sqrt{\beta_1}$.

$$\sqrt{b_1} = \frac{(n - 2)g_1}{\sqrt{n(n - 1)}} \quad (\text{Equation I.20})$$

When a distribution is symmetrical, the value of $\sqrt{b_1}$ will equal 0. When the value of $\sqrt{b_1}$ is significantly above 0, a distribution will be positively skewed, and when it is significantly below 0, a distribution will be negatively skewed. The method for determining whether a g_1 and/or $\sqrt{b_1}$ value deviates significantly from 0 is described under the **single-sample test for evaluating population skewness**. The results of the latter test, along with the results of the **single-sample test for evaluating population kurtosis**, are used in the **D'Agostino–Pearson test of**

normality (Test 5a), which is employed to assess goodness-of-fit for normality (i.e., whether sample data are likely to have been derived from a normal distribution). When a distribution is normal, both g_1 and $\sqrt{b_1}$ will equal 0.

At this point employing Equations I.17/I.18, I.19, and I.20, the values of m_3 , g_1 , and $\sqrt{b_1}$ will be computed for **Distributions A, B, and C** discussed earlier in this section. [Tables I.2–I.4](#) summarize the computations, with the following resulting values: $m_{3_A} = 0$, $m_{3_B} = -86.67$, $m_{3_C} = 86.67$, $g_{1_A} = 0$, $g_{1_B} = -1.02$, $g_{1_C} = 1.02$, and $\sqrt{b_{1_A}} = 0$, $\sqrt{b_{1_B}} = -.86$, $\sqrt{b_{1_C}} = .86$.

Table I.2 Computation of Skewness for Distribution A

X	X^2	X^3	\bar{X}	$(X - \bar{X})$	$(X - \bar{X})^2$	$(X - \bar{X})^3$
0	0	0	5	-5	25	-125
0	0	0	5	-5	25	-125
0	0	0	5	-5	25	-125
5	25	125	5	0	0	0
5	25	125	5	0	0	0
5	25	125	5	0	0	0
5	25	125	5	0	0	0
10	100	1000	5	5	25	0
10	100	1000	5	5	25	125
10	100	1000	5	5	25	125

Sums: $\Sigma X = 50$, $\Sigma X^2 = 400$, $\Sigma X^3 = 3500$, $\Sigma(X - \bar{X}) = 0$, $\Sigma(X - \bar{X})^2 = 150$, $\Sigma(X - \bar{X})^3 = 0$

$$\bar{X}_A = \frac{\Sigma X}{n} = \frac{50}{10} = 5 \quad \tilde{s}_A = \sqrt{\frac{\Sigma X^2 - \frac{(\Sigma X)^2}{n}}{n - 1}} = \sqrt{\frac{400 - \frac{(50)^2}{10}}{10 - 1}} = 4.08$$

$$m_{3_A} = \frac{n \Sigma(X - \bar{X})^3}{(n - 1)(n - 2)} = \frac{(10)(0)}{(10 - 1)(10 - 2)} = 0$$

$$m_{3_A} = \frac{n \Sigma X^3 - 3 \Sigma X \Sigma X^2 + \frac{2(\Sigma X)^3}{n}}{(n - 1)(n - 2)} = \frac{(10)(3500) - (3)(50)(400) + \frac{(2)(50)^3}{10}}{(10 - 1)(10 - 2)} = 0$$

$$g_{1_A} = \frac{m_{3_A}}{\tilde{s}_A^3} = \frac{0}{(4.08)^3} = 0 \quad \sqrt{b_{1_A}} = \frac{(n - 2)g_{1_A}}{\sqrt{n(n - 1)}} = \frac{(10 - 2)(0)}{\sqrt{10(10 - 1)}} = 0$$

Kurtosis According to D'Agostino *et al.* (1990), the word **kurtosis** means **curvature**. Kurtosis is generally defined as a measure reflecting the degree to which a distribution is **peaked**. To be more specific, kurtosis provides information regarding the height of a distribution relative to the value of its standard deviation. The most common reason for measuring kurtosis is to determine whether data are derived from a normally distributed population. Kurtosis is often described within the framework of the following three general categories, all of which are depicted by representative frequency distributions in [Figure I.2](#): **mesokurtic**, **leptokurtic**, and **platykurtic**.

A **mesokurtic** distribution, which has a degree of peakedness that is considered moderate, is represented by a **normal distribution** (i.e., the classic bell-shaped curve), which is depicted in [Figure I.3](#). All normal distributions are mesokurtic, and the weight/thickness of the tails of a normal distribution is in between the weight/thickness of the tails of distributions that are leptokurtic or platykurtic. In [Figure I.2](#), **Distribution D** best approximates a **mesokurtic** distribution.

Table I.3 Computation of Skewness for Distribution B

X	X^2	X^3	\bar{X}	$(X - \bar{X})$	$(X - \bar{X})^2$	$(X - \bar{X})^3$
0	0	0	7	-7	49	-343
1	1	1	7	-6	36	-216
1	1	1	7	-6	36	-216
9	81	729	7	2	4	8
9	81	729	7	2	4	8
10	100	1000	7	3	9	27
10	100	1000	7	3	9	27
10	100	1000	7	3	9	27
10	100	1000	7	3	9	27
10	100	1000	7	3	9	27

Sums: $\Sigma X = 70$, $\Sigma X^2 = 664$, $\Sigma X^3 = 6460$, $\Sigma(X - \bar{X}) = 0$, $\Sigma(X - \bar{X})^2 = 174$, $\Sigma(X - \bar{X})^3 = -624$

$$\bar{X}_B = \frac{\Sigma X}{n} = \frac{70}{10} = 7 \quad \tilde{s}_B = \sqrt{\frac{\Sigma X^2 - \frac{(\Sigma X)^2}{n}}{n - 1}} = \sqrt{\frac{664 - \frac{(70)^2}{10}}{10 - 1}} = 4.40$$

$$m_{3_B} = \frac{n\Sigma(X - \bar{X})^3}{(n - 1)(n - 2)} = \frac{(10)(-624)}{(10 - 1)(10 - 2)} = -86.67$$

$$m_{3_B} = \frac{n\Sigma X^3 - 3\Sigma X\Sigma X^2 + \frac{2(\Sigma X)^3}{n}}{(n - 1)(n - 2)} = \frac{(10)(6460) - (3)(70)(664) + \frac{2(70)^3}{10}}{(10 - 1)(10 - 2)} = -86.67$$

$$g_{1_B} = \frac{m_{3_B}}{\tilde{s}_B^3} = \frac{-86.67}{(4.40)^3} = -1.02 \quad \sqrt{b_{1_B}} = \frac{(n - 2)g_{1_B}}{\sqrt{n(n - 1)}} = \frac{(10 - 2)(-1.02)}{\sqrt{(10)(10 - 1)}} = -.86$$

A **leptokurtic** distribution is characterized by a high degree of peakedness. The scores in a leptokurtic distribution tend to be clustered much more closely around the mean than they are in either a mesokurtic or platykurtic distribution. Because of the latter, the value of the standard deviation for a leptokurtic distribution will be smaller than the standard deviation for the latter two distributions (if we assume the range of scores in all three distributions is approximately the same). The tails of a leptokurtic distribution are heavier/thicker than the tails of a mesokurtic distribution. In [Figure I.2](#), **Distribution E** best approximates a **leptokurtic** distribution.

A **platykurtic** distribution is characterized by a low degree of peakedness. The scores in a platykurtic distribution tend to be spread out more from the mean than they are in either a mesokurtic or leptokurtic distribution. Because of the latter, the value of the standard deviation for a platykurtic distribution will be larger than the standard deviation for the latter two distributions (if we assume the range of scores in all three distributions is approximately the same). The tails of a platykurtic distribution are lighter/thinner than the tails of a mesokurtic distribution. In [Figure I.2](#), **Distribution F** best approximates a **platykurtic** distribution.

Moors (1986) defines kurtosis as the degree of dispersion between the points marked off on the abscissa (X -axis) that correspond to $\mu \pm \sigma$. Thus, with respect to the three types of distributions, we can make the statement that the range of values on the abscissa that fall between the population mean (μ) and one standard deviation above and below the mean will be greatest for a platykurtic distribution and smallest for a leptokurtic distribution, with a mesokurtic distribution being in the middle. As will be noted later in the **Introduction**, in the case of a normal distribution (which, as noted earlier, will always be mesokurtic), approximately 68% of the scores will always fall between the mean and one standard deviation above and below the mean.

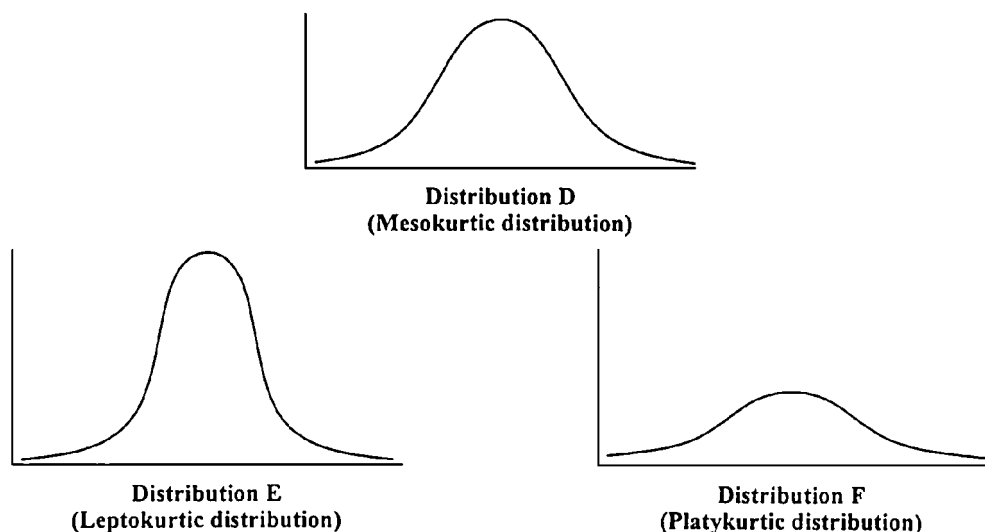


Figure I.2 Representative Types of Kurtosis

Table I.4 Computation of Skewness for Distribution C

X	X^2	X^3	\bar{X}	$(X - \bar{X})$	$(X - \bar{X})^2$	$(X - \bar{X})^3$
0	0	0	3	-3	9	-27
0	0	0	3	-3	9	-27
0	0	0	3	-3	9	-27
0	0	0	3	-3	9	-27
0	0	0	3	-3	9	-27
1	1	1	3	-2	4	-8
1	1	1	3	-2	4	-8
9	81	729	3	6	36	216
9	81	729	3	6	36	216
10	100	1000	3	7	49	343

Sums: $\Sigma X = 30$, $\Sigma X^2 = 264$, $\Sigma X^3 = 2460$, $\Sigma(X - \bar{X}) = 0$, $\Sigma(X - \bar{X})^2 = 174$, $\Sigma(X - \bar{X})^3 = 624$

$$\bar{X}_C = \frac{\Sigma X}{n} = \frac{30}{10} = 3 \quad \tilde{s}_C = \sqrt{\frac{\Sigma X^2 - \frac{(\Sigma X)^2}{n}}{n - 1}} = \sqrt{\frac{264 - \frac{(30)^2}{10}}{10 - 1}} = 4.40$$

$$m_{3_C} = \frac{n \Sigma(X - \bar{X})^3}{(n - 1)(n - 2)} = \frac{(10)(624)}{(10 - 1)(10 - 2)} = 86.67$$

$$m_{3_C} = \frac{n \Sigma X^3 - 3 \Sigma X \Sigma X^2 + \frac{2(\Sigma X)^3}{n}}{(n - 1)(n - 2)} = \frac{(10)(2460) - (3)(30)(264) + \frac{2(30)^3}{10}}{(10 - 1)(10 - 2)} = 86.67$$

$$g_{1_C} = \frac{m_{3_C}}{\tilde{s}_C^3} = \frac{86.67}{(4.40)^3} = 1.02 \quad \sqrt{b_{1_C}} = \frac{(n - 2)g_{1_C}}{\sqrt{n(n - 1)}} = \frac{(10 - 2)(1.02)}{\sqrt{(10)(10 - 1)}} = .86$$

One crude way of estimating kurtosis is that if the standard deviation of a unimodal symmetrical distribution is approximately one-sixth the value of the range of the distribution, the distribution is mesokurtic. In the case of a leptokurtic distribution, the standard deviation will be substantially less than one-sixth of the range, while in the case of a platykurtic distribution the standard deviation will be substantially greater than one-sixth of the range. To illustrate, let us assume that the range of values on an IQ test administered to a large sample is 90 points (e.g., the IQ scores fall in the range 55 to 145). If the standard deviation for the sample equals 15, the distribution would be mesokurtic (since $15/90 = 1/6$). If the standard deviation equals 5, the distribution would be leptokurtic (since $5/90 = 1/18$, which is substantially less than $1/6$). If the standard deviation equals 30, the distribution would be platykurtic (since $30/90 = 1/3$, which is substantially greater than $1/6$).

A number of alternative measures for kurtosis have been developed, including one developed by Moors (1988) and described in Zar (1999). The latter measure computes kurtosis by employing specific quantile values in the distribution. The most precise measure of kurtosis, however, employs the exact value of the fourth moment about the mean, designated earlier as m_4 . Cohen (1996) and Zar (1999) note that the unbiased estimate of the population parameter estimated by m_4 can be computed with either Equation I.21 (which is the definitional equation) or Equation I.22 (which is a computational equation).

(Equation I.21)

$$m_4 = \frac{[\sum(X - \bar{X})^4(n)(n + 1)]/(n - 1)] - 3[\sum(X - \bar{X})^2]^2}{(n - 2)(n - 3)}$$

(Equation I.22)

$$m_4 = \frac{(n^3 + n^2)\sum X^4 - 4(n^2 + n)\sum X^3\sum X - 3(n^2 - n)(\sum X^2)^2 + 12n\sum X^2(\sum X)^2 - 6(\sum X)^4}{n(n - 1)(n - 2)(n - 3)}$$

Note that in Equation I.21, the notation $\sum(X - \bar{X})^4$ indicates that the mean is subtracted from each of the n scores in the distribution, each difference score is raised to the fourth power, and the n difference scores raised to the fourth power are summed. The notation $\sum X^4$ in Equation I.22 indicates each of the n scores is raised to the fourth power, and the n resulting values are summed. The notation $(\sum X)^4$ in Equation I.22 indicates that the n scores are summed, and the resulting value is raised to the fourth power. Note that the minimum sample size required to compute kurtosis is $n = 4$, since any lower value will result in a zero in the denominators of Equations I.21 and I.22, rendering them insoluble.

Since the value computed for m_4 is in units of the fourth power, the unitless statistic g_2 , which is an estimate of the population parameter γ_2 , is commonly employed to express kurtosis. The value of g_2 is computed with Equation I.23.

$$g_2 = \frac{m_4}{\tilde{s}^4} \quad \text{(Equation I.23)}$$

When a distribution is mesokurtic the value of g_2 will equal 0. When the value of g_2 is significantly above 0, a distribution will be leptokurtic, and when it is significantly below 0, a distribution will be platykurtic.

Zar (1999) notes that a population parameter designated β_2 is employed by some sources (e.g., Anscombe and Glynn (1983), D'Agostino (1986), and D'Agostino *et al.* (1990)) to represent kurtosis. Equation I.24 is used to compute b_2 , which is the sample statistic employed to estimate the value of β_2 .

$$b_2 = \frac{(n-2)(n-3)g_2}{(n+1)(n-1)} + \frac{3(n-1)}{n+1} \quad (\text{Equation I.24})$$

When a distribution is mesokurtic, the value of b_2 will equal $[3(n-1)]/(n+1)$. Inspection of the latter equation reveals that as the value of the sample size increases, the value of b_2 approaches 3. When the value computed for b_2 is significantly below $[3(n-1)]/(n+1)$, a distribution will be platykurtic. When the value computed for b_2 is significantly greater than $[3(n-1)]/(n+1)$, a distribution will be leptokurtic. The method for determining whether a g_2 and/or b_2 value is **statistically significant** is described under the **single-sample test for evaluating population kurtosis** (the concept of **statistical significance** is discussed in the latter part of the **Introduction**). The results of the latter test, along with the results of the **single-sample test for evaluating population skewness**, are used in the **D'Agostino-Pearson test of normality**, which is employed to assess goodness-of-fit for normality. As noted earlier, a normal distribution will always be mesokurtic, with $g_2 = 0$ and $b_2 = 3$.

At this point employing Equations I.21/I.22, I.23 and I.24, the values of m_4 , g_2 , and b_2 will be computed for two distributions to be designated **E** and **F**. The data for **Distributions E** and **F** are designed (within the framework of a small sample size with $n = 20$) to approximate a **leptokurtic distribution** and **platykurtic distribution** respectively. [Tables I.5](#) and [I.6](#) summarize the computations, with the following resulting values: $m_{4_E} = 307.170$, $m_{4_F} = -1181.963$, $g_{2_E} = 3.596$, $g_{2_F} = -.939$, and $b_{2_E} = 5.472$, $b_{2_F} = 1.994$.

The Normal Distribution

When an inferential statistical test is employed with one or more samples to draw inferences about one or more populations, such a test may make certain assumptions about the shape of an underlying population distribution. The most commonly encountered assumption in this regard is that a distribution is **normal**. When viewed from a visual perspective, the **normal distribution** (which as noted earlier is often referred to as the **bell-shaped curve**) is a graph of a frequency distribution which can be described mathematically and observed empirically (insofar as many variables in the real world appear to be distributed normally). The shape of the normal distribution is such that the closer a score is to the mean, the more frequently it occurs. As scores deviate more and more from the mean (i.e., become higher or lower), the more extreme the score, the lower the frequency with which that score occurs. As noted earlier, a normal distribution will always be symmetrical (with $\gamma_1 = g_1 = 0$ and $\sqrt{\beta_1} = \sqrt{b_1} = 0$) and mesokurtic (with $\gamma_2 = g_2 = 0$ and $\beta_2 = b_2 = 3$).

Any normal distribution can be converted into what is referred to as the **standard normal distribution**, by assigning it a mean value of 0 (i.e., $\mu = 0$) and a standard deviation of 1 (i.e., $\sigma = 1$). The **standard normal distribution**, which is represented in [Figure I.3](#), is employed more frequently in inferential statistics than any other theoretical probability distribution. The use of the term theoretical probability distribution in this context is based on the fact that it is known that in the standard normal distribution (or, for that matter, any normal distribution) a certain proportion of cases will always fall within specific areas of the curve. As a result of this, if one knows how far removed a score is from the mean of the distribution, one can specify the proportion of cases that obtain that score, as well as the likelihood of randomly selecting a subject or object with that score.

The general equation for the normal distribution is Equation I.25.

$$Y = \frac{1}{\sigma\sqrt{2\pi}} e^{-(X - \mu)^2/2\sigma^2} \quad (\text{Equation I.25})$$

Table I.5 Computation of Kurtosis for Distribution E

X	X^2	X^3	X^4	\bar{X}	$(X - \bar{X})$	$(X - \bar{X})^2$	$(X - \bar{X})^4$
2	4	8	16	10	-8	64	4096
7	49	343	2401	10	-3	9	81
8	64	512	4096	10	-2	4	16
8	64	512	4096	10	-2	4	16
8	64	512	4096	10	-2	4	16
9	81	729	6561	10	-1	1	1
9	81	729	6561	10	-1	1	1
9	81	729	6561	10	-1	1	1
10	100	1000	10000	10	0	0	0
10	100	1000	10000	10	0	0	0
10	100	1000	10000	10	0	0	0
10	100	1000	10000	10	0	0	0
11	121	1331	14641	10	1	1	1
11	121	1331	14641	10	1	1	1
11	121	1331	14641	10	1	1	1
12	144	1728	20736	10	2	4	16
12	144	1728	20736	10	2	4	16
12	144	1728	20736	10	2	4	16
13	169	2197	28561	10	3	9	81
18	324	5832	104976	10	8	64	4096

Sums: $\Sigma X = 200$, $\Sigma X^2 = 2176$, $\Sigma X^3 = 25280$, $\Sigma X^4 = 314056$

$\Sigma(X - \bar{X}) = 0$, $\Sigma(X - \bar{X})^2 = 176$, $\Sigma(X - \bar{X})^4 = 8456$

$$\bar{X}_E = \frac{\Sigma X}{n} = \frac{200}{20} = 10 \quad \tilde{s}_E = \sqrt{\frac{\Sigma X^2 - \frac{(\Sigma X)^2}{n}}{n - 1}} = \sqrt{\frac{2176 - \frac{(200)^2}{20}}{20 - 1}} = 3.04$$

$$m_{4_E} = \frac{[[\Sigma(X - \bar{X})^4(n)(n + 1)]/(n - 1)] - 3[\Sigma(X - \bar{X})^2]^2}{(n - 2)(n - 3)}$$

$$= \frac{[[(8456)(20)(20 + 1)]/(20 - 1)] - 3(176)^2}{(20 - 2)(20 - 3)} = 307.170$$

$$m_{4_E} = \frac{(n^3 + n^2)\Sigma X^4 - 4(n^2 + n)\Sigma X^3\Sigma X - 3(n^2 - n)(\Sigma X^2)^2 + 12n\Sigma X^2(\Sigma X)^2 - 6(\Sigma X)^4}{n(n - 1)(n - 2)(n - 3)}$$

$$= \frac{[(20)^3 + (20)^2](314056) - 4[(20)^2 + 20](25280)(200) - 3[(20)^2 - 20](2176)^2 + 12(20)(2176)(200)^2 - 6(200)^4]}{[(20)(20 - 1)(20 - 2)(20 - 3)]} = 307.170$$

$$g_{2_E} = \frac{m_{4_E}}{\tilde{s}_E^4} = \frac{307.170}{(3.04)^4} = 3.596$$

$$b_{2_E} = \frac{(n - 2)(n - 3)g_{2_E}}{(n + 1)(n - 1)} + \frac{3(n - 1)}{(n + 1)} = \frac{(20 - 2)(20 - 3)(3.596)}{(20 + 1)(20 - 1)} + \frac{3(20 - 1)}{(20 + 1)} = 5.472$$

Table I.6 Computation of Kurtosis for Distribution F

X	X^2	X^3	X^4	\bar{X}	$(X - \bar{X})$	$(X - \bar{X})^2$	$(X - \bar{X})^4$
0	0	0	0	10	-10	100	10000
1	1	1	1	10	-9	81	6561
3	9	27	81	10	-7	49	2401
3	9	27	81	10	-7	49	2401
5	25	125	625	10	-5	25	625
5	25	125	625	10	-5	25	625
8	64	512	4096	10	-2	4	16
8	64	512	4096	10	-2	4	16
10	100	1000	10000	10	0	0	0
10	100	1000	10000	10	0	0	0
10	100	1000	10000	10	0	0	0
10	100	1000	10000	10	0	0	0
12	144	1728	20736	10	2	4	16
12	144	1728	20736	10	2	4	16
15	225	3375	50625	10	5	25	625
15	225	3375	50625	10	5	25	625
17	289	4913	83521	10	7	49	2401
17	289	4913	83521	10	7	49	2401
19	361	6859	130321	10	9	81	6561
20	400	8000	160000	10	10	100	10000

Sums: $\Sigma X = 200$, $\Sigma X^2 = 2674$, $\Sigma X^3 = 40220$, $\Sigma X^4 = 649690$

$\Sigma(X - \bar{X}) = 0$, $\Sigma(X - \bar{X})^2 = 674$, $\Sigma(X - \bar{X})^4 = 45290$

$$\bar{X}_F = \frac{\Sigma X}{n} = \frac{200}{20} = 10 \quad \tilde{s}_F = \sqrt{\frac{\Sigma X^2 - \frac{(\Sigma X)^2}{n}}{n - 1}} = \sqrt{\frac{2674 - \frac{(200)^2}{20}}{20 - 1}} = 5.96$$

$$m_{4_F} = \frac{[[\Sigma(X - \bar{X})^4(n + 1)]/(n - 1)] - 3[\Sigma(X - \bar{X})^2]^2}{(n - 2)(n - 3)}$$

$$= \frac{[[(45290)(20)(20 + 1)] / (20 - 1)] - 3(674)^2}{(20 - 2)(20 - 3)} = -1181.963$$

$$m_{4_F} = \frac{(n^3 + n^2)\Sigma X^4 - 4(n^2 + n)\Sigma X^3\Sigma X - 3(n^2 - n)(\Sigma X^2)^2 + 12n\Sigma X^2(\Sigma X)^2 - 6(\Sigma X)^4}{n(n - 1)(n - 2)(n - 3)}$$

$$= \frac{[(20)^3 + (20)^2](649690) - 4[(20)^2 + 20](40220)(200) - 3[(20)^2 - 20](2674)^2 + 12(20)(2674)(200)^2 - 6(200)^4]}{[(20)(20 - 1)(20 - 2)(20 - 3)]} = -1181.963$$

$$g_{2_F} = \frac{m_{4_F}}{\tilde{s}_F^4} = \frac{-1181.963}{(5.96)^4} = -.939$$

$$b_{2_F} = \frac{(n - 2)(n - 3)g_{2_F}}{(n + 1)(n - 1)} + \frac{3(n - 1)}{(n + 1)} = \frac{(20 - 2)(20 - 3)(-.939)}{(20 + 1)(20 - 1)} + \frac{3(20 - 1)}{(20 + 1)} = 1.994$$

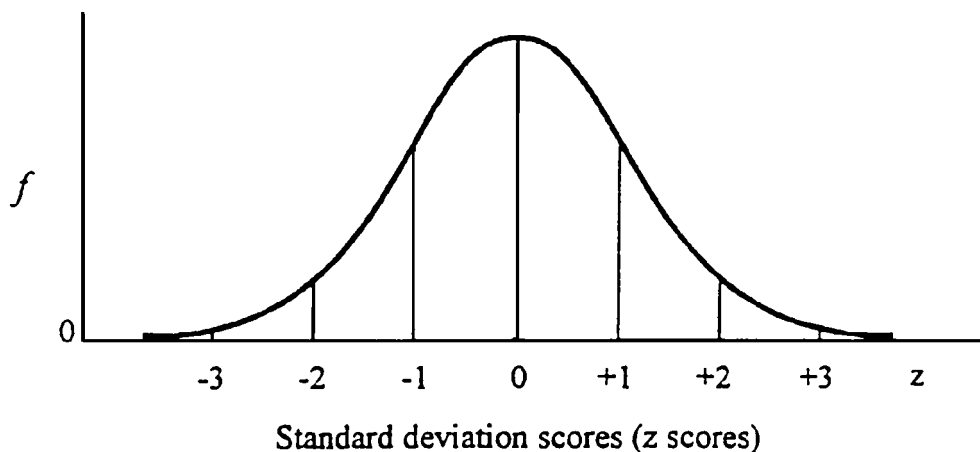


Figure I.3 The Standard Normal Distribution

In Equation I.25 the symbols μ and σ represent the mean and standard deviation of a normal distribution. For any normal distribution where the values of μ and σ are known, a value of Y (which represents the height of the distribution at a given point on the abscissa) can be computed simply by substituting a specified value of X in Equation I.25. Note that in the case of the standard normal distribution, where $\mu = 0$ and $\sigma = 1$, Equation I.25 becomes Equation I.26.⁵

$$Y = \frac{1}{\sqrt{2\pi}} e^{-X^2/2} \quad (\text{Equation I.26})$$

The reader should take note of the fact that the normal distribution is a family of distributions which is comprised of all possible values of μ and σ that can be substituted in Equation I.25. Although the values of μ and σ for a normal distribution may vary, as noted earlier, all normal distributions are mesokurtic.

For any variable that is normally distributed, regardless of the values of the population mean and standard deviation, the distance of a score from the mean in standard deviation units can be computed with Equation I.27. The z value computed with Equation I.27 is a measure in standard deviation units of how far a score is from the mean.

$$z = \frac{X - \mu}{\sigma} \quad (\text{Equation I.27})$$

Where: X is a specific score
 μ is the value of the population mean
 σ is the value of the population standard deviation

When Equation I.27 is employed, any score that is above the mean will yield a positive z score, and any score that is below the mean will yield a negative z score. Any score that is equal to the mean will yield a z score of zero.

To illustrate this, assume we have an IQ test for which it is known that the population mean is $\mu = 100$ and the population standard deviation is $\sigma = 15$. Assume three people take the test and obtain the following IQ scores: **Person A:** 135; **Person B:** 65; and **Person C:** 100. The z score (standard deviation score) for each person is computed below. The reader should take note of

the fact that a z score is always computed to at least two decimal places.

$$\text{Person A: } z = \frac{135 - 100}{15} = 2.33$$

$$\text{Person B: } z = \frac{65 - 100}{15} = -2.33$$

$$\text{Person C: } z = \frac{100 - 100}{15} = 0$$

Person A obtains an IQ score that is 2.33 standard deviation units above the mean, Person B obtains an IQ score that is 2.33 standard deviation units below the mean, and Person C obtains an IQ score at the mean. If we wanted to determine the likelihood (i.e., the probability) of selecting a person (as well as the proportion of people) who obtains a specific score in a normal distribution, **Table A1 (Table of the Normal Distribution)** in the **Appendix** can provide this information. Although **Table A1** is comprised of four columns, for the analysis to be discussed in this section we will only be interested in the first three columns.

Column 1 in **Table A1** lists z scores that range in value from 0 to an **absolute value** of 4. The use of the term **absolute value of 4** is based on the fact that since the normal distribution is symmetrical, anything we say with respect to the probability or the proportion of cases associated with a positive z score will also apply to the corresponding negative z score. Note that positive z scores will always fall to the right of the mean (often referred to as the **right tail** of the distribution), thus indicating that the score is above the mean. Negative z scores, on the other hand, will always fall to the left of the mean (often referred to as the **left tail** of the distribution), thus indicating that the score is below the mean.⁶

Column 2 in **Table A1** lists the proportion of cases (which can also be interpreted as probability values) that falls between the mean of the distribution and the z score that appears in a specific row.

Column 3 in the table lists the proportion of cases that falls beyond the z score in that row. More specifically, the proportion listed in Column 3 is evaluated in relation to the tail of the distribution in which the score appears. Thus, if a z score is positive, the value in Column 3 will represent the proportion of cases that falls above that z score, whereas if the z score is negative, the value in Column 3 will represent the proportion of cases that falls below that z score.⁷

Table A1 will now be employed in reference to the IQ scores of Person A and Person B. For both subjects the computed absolute value of z associated with their IQ score is $z = 2.33$. For $z = 2.33$, the tabled values in Columns 2 and 3, are respectively, .4901 and .0099. The value in Column 2 indicates that the proportion of the population that obtains a z score between the mean and $z = 2.33$ is .4901 (which expressed as a percentage is 49.01%),⁸ and the proportion of the population which obtains a z score between the mean and $z = -2.33$ is .4901. We can make comparable statements with respect to the IQ values associated with these z scores. Thus, we can say that the proportion of the population that obtains an IQ score between 100 and 135 is .4901, and the proportion of the population which obtains an IQ score between 65 and 100 is .4901. Since the normal distribution is symmetrical, .5 (or 50%) represents the proportion of cases that falls both above and below the mean. Thus, we can determine that $.5 + .4901 = .9901$ (or 99.01%) is the proportion of people with an IQ of 135 or less, as well as the proportion of people who have an IQ of 65 or greater. We can state that a person who has an IQ of 135 has a score that falls at approximately the 99th percentile, since it is equal to or greater than the scores of 99% of the population. On the other hand, a person who has an IQ of 65 has a score that falls at the 1st

percentile, since it is equal to or greater than the scores of only approximately 1% of the population.

The value in Column 3 indicates that the proportion of the population that obtains a score of $z = 2.33$ or greater (and thus, in reference to Person A, an IQ of 135 or greater) is .0099 (which is .99%). In the same respect, the proportion of the population that obtains a score of $z = -2.33$ or less (and thus, in reference to Person B, an IQ of 65 or less) is .0099.

If one interprets the values in Columns 2 and 3 as probability values instead of proportions, we can state that if one randomly selects a person from the population, the probability of selecting someone with an IQ of 135 or greater will be approximately 1%. In the same respect, the probability of selecting someone with an IQ of 65 or less will also be approximately 1%.

In the case of Person C, whose IQ score of 100 results in the standard deviation score $z = 0$, inspection of [Table A1](#) reveals that the values in Columns 2 and 3 associated with $z = 0$ are, respectively, .0000 and .5000. This indicates that the proportion of the population that obtains an IQ of 100 or greater is .5 (which is equivalent to 50%), and that the proportion of the population which obtains an IQ of 100 or less is .5. Thus, if we randomly select a person from the population, the probability of selecting someone with an IQ equal to or greater than 100 will be .5, and the probability of selecting someone with an IQ equal to or less than 100 will be .5. We can also state that the score of a person who has an IQ of 100 falls at the 50th percentile, since it is equal to or greater than the scores of 50% of the population.

Note that to determine a percentile rank associated with a positive z value (or a score that results in a positive z value), 50% should be added to the percentage of cases that fall between the mean and that z value — in other words, the entry for the z value in Column 2 expressed as a percentage is added to 50%. The 50% we add to the value in Column 2 represents the percentage of the population that scores below the mean. The percentile rank for a negative z value (or a score that results in a negative z value) is the entry in Column 3 for that z value expressed as a percentage.

[Figure I.4](#) provides a graphic summary of the proportions discussed in the above analysis.

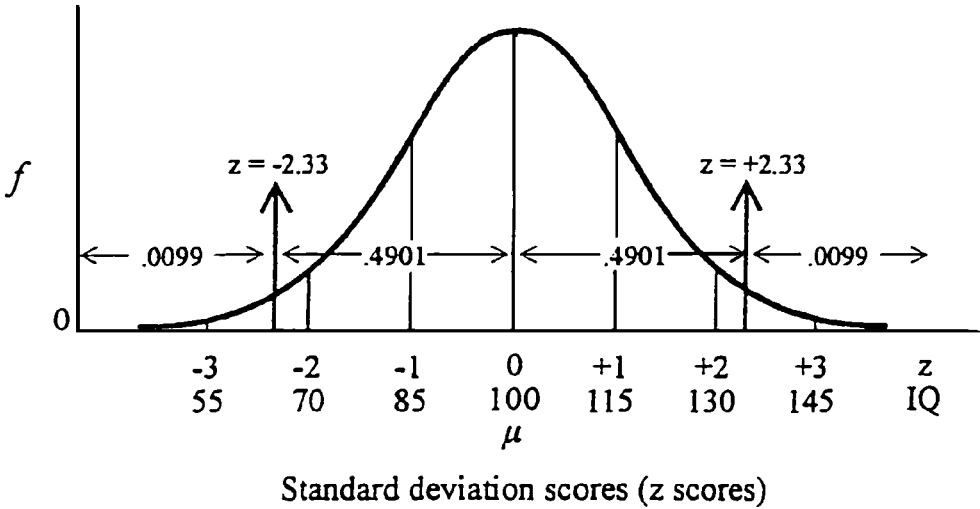


Figure I.4 Summary of Normal Curve Problem

Hypothesis Testing

Inferential statistics primarily employ sample data in two ways to draw inferences about one or more populations. The two methodologies employed in inferential statistics are **hypothesis testing** and **estimation of population parameters**. This section will discuss hypothesis testing.

Within the framework of inferential statistics, a **hypothesis** can be defined as a prediction about a single population or about the relationship between two or more populations. **Hypothesis testing** is a procedure in which sample data are employed to evaluate a hypothesis. In using the term hypothesis, some sources make a distinction between a **research hypothesis** and **statistical hypotheses**.

A **research hypothesis** is a general statement of what a researcher predicts. Two examples of a research hypothesis are: a) The average IQ of all males is some value other than 100; and b) Clinically depressed patients who take an antidepressant for six months will be less depressed than clinically depressed patients who take a placebo for six months.

In order to evaluate a research hypothesis, it is restated within the framework of two **statistical hypotheses**. Through use of a symbolic format, the statistical hypotheses summarize the research hypothesis with reference to the population parameter or parameters under study. The two statistical hypotheses are the **null hypothesis**, which is represented by the notation H_0 and, the **alternative hypothesis**, which is represented by the notation H_1 .

The **null hypothesis** is a statement of **no effect** or **no difference**. Since the statement of the research hypothesis generally predicts the presence of an effect or a difference with respect to whatever it is that is being studied, the null hypothesis will generally be a hypothesis that the researcher expects to be rejected. The **alternative hypothesis**, on the other hand, represents a statistical statement indicating the **presence of an effect or a difference**. Since the research hypothesis typically predicts an effect or difference, the researcher generally expects the alternative hypothesis to be supported.

The null and alternative hypotheses will now be discussed in reference to the two research hypotheses noted earlier. Within the framework of the first research hypothesis that was presented, we will assume that a study is conducted in which an IQ score is obtained for each of n males who have been randomly selected from a population comprised of N males. The null and alternative hypotheses can be stated as follows: $H_0: \mu = 100$ and $H_1: \mu \neq 100$. The null hypothesis states that the mean (IQ score) of the population the sample represents equals 100. The alternative hypothesis states that the mean of the population the sample represents does not equal 100. The absence of an effect will be indicated by the fact that the sample mean is equal to or reasonably close to 100. If such an outcome is obtained, a researcher can be reasonably confident that the sample has come from a population with a mean value of 100. The presence of an effect, on the other hand, will be indicated by the fact that the sample mean is significantly above or below the value 100. Thus, if the sample mean is substantially larger or smaller than 100, the researcher can conclude there is a high likelihood that the population mean is some value other than 100, and thus reject the null hypothesis.

As stated above, the alternative hypothesis is **nondirectional**. A **nondirectional** (also referred to as a **two-tailed**) **alternative hypothesis** does not make a prediction in a specific direction. The alternative hypothesis $H_1: \mu \neq 100$ just states that the population mean will not equal 100, but it does not predict whether it will be less than or greater than 100. If, however, a researcher wants to make a prediction with respect to direction, the alternative hypothesis can also be stated **directionally**. Thus, with respect to the above example, either of the following two **directional** (also referred to as **one-tailed**) **alternative hypotheses** can be employed: $H_1: \mu > 100$ or $H_1: \mu < 100$.

The alternative hypothesis $H_1: \mu > 100$ states that the mean of the population the sample

represents is some value greater than 100. If the directional alternative hypothesis $H_1: \mu > 100$ is employed, the null hypothesis can only be rejected if the data indicate that the population mean is some value above 100. The null hypothesis cannot, however, be rejected if the data indicate that the population mean is some value below 100.

The alternative hypothesis $H_1: \mu < 100$ states that the mean of the population the sample represents is some value less than 100. If the directional alternative hypothesis $H_1: \mu < 100$ is employed, the null hypothesis can only be rejected if the data indicate that the population mean is some value below 100. The null hypothesis cannot, however, be rejected if the data indicate that the population mean is some value above 100. The reader should take note of the fact that although there are three possible alternative hypotheses that one can employ (one that is non-directional and two that are directional), the researcher will select only one of the alternative hypotheses.

Researchers are not in agreement with respect to the conditions under which one should employ a nondirectional or a directional alternative hypothesis. Some researchers take the position that a nondirectional alternative hypothesis should always be employed, regardless of one's prior expectations about the outcome of an experiment. Other researchers believe that a non-directional alternative hypothesis should only be employed when one has no prior expectations about the outcome of an experiment (i.e., no expectation with respect to the direction of an effect or difference). These same researchers believe that if one does have a definite expectation about the direction of an effect or difference, a directional alternative hypothesis should be employed. One advantage of employing a directional alternative hypothesis is that in order to reject the null hypothesis, a directional alternative hypothesis does not require that there be as large an effect or difference in the sample data as will be the case if a nondirectional alternative hypothesis is employed.

The second of the research hypotheses discussed earlier in this section predicted that an antidepressant will be more effective than a placebo in treating depression. Let us assume that in order to evaluate this research hypothesis, a study is conducted which involves two groups of clinically depressed patients. One group, which will represent Sample 1, is comprised of n_1 patients, and the other group, which will represent Sample 2, is comprised of n_2 patients. The subjects in Sample 1 take an antidepressant for six months, and the subjects in Sample 2 take a placebo during the same period of time. After six months have elapsed, each subject is assigned a score with respect to his or her level of depression.

The null and alternative hypotheses can be stated as follows: $H_0: \mu_1 = \mu_2$ and $H_1: \mu_1 \neq \mu_2$. The null hypothesis states that the mean (depression score) of the population Sample 1 represents equals the mean of the population Sample 2 represents. The alternative hypothesis (which is stated **nondirectionally**) states that the mean of the population Sample 1 represents does not equal the mean of the population Sample 2 represents. In this instance the two populations are a population comprised of N_1 clinically depressed people who take an antidepressant for six months versus a population comprised of N_2 clinically depressed people who take a placebo for six months. The absence of an effect or difference will be indicated by the fact that the two sample means are exactly the same value or close to being equal. If such an outcome is obtained, a researcher can be reasonably confident that the samples do not represent two different populations.⁹ The presence of an effect, on the other hand, will be indicated if a significant difference is observed between the two sample means. Thus, we can reject the null hypothesis if the mean of Sample 1 is significantly larger than the mean of Sample 2, or the mean of Sample 1 is significantly smaller than the mean of Sample 2.

As is the case with the first research hypothesis discussed earlier, the alternative hypothesis can also be stated directionally. Thus, either of the following two directional alternative hypotheses can be employed: $H_1: \mu_1 > \mu_2$ or $H_1: \mu_1 < \mu_2$.

The alternative hypothesis $H_1: \mu_1 > \mu_2$ states that the mean of the population Sample 1 represents is greater than the mean of the population Sample 2 represents. If the directional alternative hypothesis $H_1: \mu_1 > \mu_2$ is employed, the null hypothesis can only be rejected if the data indicate that the mean of Sample 1 is significantly greater than the mean of Sample 2. The null hypothesis cannot, however, be rejected if the mean of Sample 1 is significantly less than the mean of Sample 2.

The alternative hypothesis $H_1: \mu_1 < \mu_2$ states that the mean of the population Sample 1 represents is less than the mean of the population Sample 2 represents. If the directional alternative hypothesis $H_1: \mu_1 < \mu_2$ is employed, the null hypothesis can only be rejected if the data indicate that the mean of Sample 1 is significantly less than the mean of Sample 2. The null hypothesis cannot, however, be rejected if the mean of Sample 1 is significantly greater than the mean of Sample 2.

Upon collecting the data for a study, the next step in the hypothesis testing procedure is to evaluate the data through use of the appropriate inferential statistical test. An inferential statistical test yields a **test statistic**. The latter value is interpreted by employing special tables that contain information with regard to the expected distribution of the test statistic. More specifically, such tables contain extreme values of the test statistic (referred to as **critical values**) that are highly unlikely to occur if the null hypothesis is true. Such tables allow a researcher to determine whether or not the result of a study is **statistically significant**.

The term **statistical significance** implies that one is determining whether an obtained difference in an experiment is due to chance or is the result of a genuine experimental effect. To clarify this, think of a roulette wheel on which there are 38 possible numbers that may occur on any roll of the wheel. Suppose we spin a wheel 38,000 times. On the basis of chance each number should occur $1/38^{\text{th}}$ of the time, and thus each value should occur 1000 times (i.e., $38000 \div 38$). Suppose the number 32 occurs 998 times in 38,000 spins of the wheel. Since this value is close to the expected value of 1000, it is highly unlikely that the wheel is biased against the number 32, and is thus not a fair wheel (at least in reference to the number 32). This is because 998 is extremely close to 1000, and a difference of 2 outcomes isn't unlikely on the basis of the random occurrence of events (i.e., chance). On the other hand, if the number 32 only occurs 380 times in 38,000 trials (i.e., $1/100^{\text{th}}$ of the time), since 380 is well below the expected value of 1000, this strongly suggests that the wheel is biased against the number 32 (and is thus probably biased in favor of one or more of the other numbers). On the basis of this, one would probably conclude that the wheel is defective and should be replaced.

When evaluating the results of an experiment, one employs a logical process similar to that involved in the above situation with the roulette wheel. The decision on whether to retain or reject the null hypothesis is based on contrasting the observed outcome of an experiment with the outcome one can expect if, in fact, the null hypothesis is true. This decision is made by using the appropriate inferential statistical test. An inferential statistical test is essentially an equation which describes a set of mathematical operations that are to be performed on the data obtained in a study. The end result of conducting such a test is a final value which is designated as the **test statistic**. A test statistic is evaluated in reference to a **sampling distribution**, which is a theoretical probability distribution of all the possible values the test statistic can assume if one were to conduct an infinite number of studies employing a sample size equal to that used in the study being evaluated. The probabilities in a sampling distribution are based on the assumption that each of the samples is randomly drawn from the population it represents.

When evaluating the study involving the use of a drug versus a placebo in treating depression, one is asking if the difference between the scores of the two groups is due to chance, or if instead, it is due to some nonchance factor (which in a well controlled study will be the differential treatment to which the groups are exposed). The larger the difference between the average

scores of the two groups (just like the larger the difference between the observed and expected occurrence of a number on a roulette wheel), the less likely the difference is due to chance factors, and the more likely it is due to the experimental treatments. Thus, by declaring a difference statistically significant, the researcher is saying that based on an analysis of the sampling distribution of the test statistic, it is highly unlikely that a difference equal to or greater than that which was observed in the study could have occurred as result of chance. In view of this, the most logical decision is to conclude that the difference is due to the experimental treatments, and thus reject the null hypothesis.

Scientific convention has established that in order to declare a difference statistically significant, there can be no more than a 5% likelihood that the difference is due to chance. If a researcher believes that 5% is too high a value, one may elect to employ a 1%, or an even lower minimum likelihood, before one will be willing to conclude that a difference is significant. The notation $p > .05$ is employed to indicate that the result of an experiment is not significant. This notation indicates that there is a greater than 5% likelihood that an observed difference or effect could be due to chance. On the other hand, the notation $p < .05$ indicates that the outcome of a study is significant at the .05 level.¹⁰ This indicates that there is less than a 5% likelihood that an obtained difference or effect can be due to chance. The notation $p < .01$ indicates a significant result at the .01 level (i.e., there is less than a 1% likelihood that the difference is due to chance).

When the normal distribution is employed for inferential statistical analysis, four tabled critical values are commonly employed. These values are summarized in [Table I.7](#).

Table I.7 Tabled Critical Two-Tailed and One-Tailed .05 and .01 z Values

	$z_{.05}$	$z_{.01}$
Two-tailed values	1.96	2.58
One-tailed values	1.65	2.33

The value $z = 1.96$ is referred to as the tabled critical two-tailed .05 z value. This value is employed since the total proportion of cases in the normal distribution that falls above $z = +1.96$ or below $z = -1.96$ is .05. This can be confirmed by examining Column 3 of [Table A1](#) for the value $z = 1.96$. The value of .025 in Column 3 indicates that the proportion of cases in the right tail of the curve that falls above $z = +1.96$ is .025, and the proportion of cases in the left tail of the curve that falls below $z = -1.96$ is .025. If the two .025 values are added, the resulting proportion is .05. Note that this is a two-tailed critical value, since the proportion .05 is based on adding the extreme 2.5% of the cases from the two tails of the distribution.

The value $z = 2.58$ is referred to as the tabled critical two-tailed .01 z value. This value is employed since the total proportion of cases in the normal distribution that falls above $z = +2.58$ or below $z = -2.58$ is .01. This can be confirmed by examining Column 3 of [Table A1](#) for the value $z = 2.58$. The value of .0049 (which rounded off equals .005) in Column 3 indicates that the proportion of cases in the right tail of the curve that falls above $z = +2.58$ is .0049, and the proportion of cases in the left tail of the curve that falls below $z = -2.58$ is .0049. If the two .0049 values are added, the resulting proportion is .0098, which rounded off equals .01. Note that this is a two-tailed critical value, since the proportion .01 is based on adding the extreme .5% of the cases from the two tails of the distribution.

The value $z = 1.65$ is referred to as the tabled critical one-tailed .05 z value. This value is employed since the proportion of cases in the normal distribution that falls above $z = +1.65$ or below $z = -1.65$ in each tail of the distribution is .05. This can be confirmed by examining Column 3 of [Table A1](#) for the value $z = 1.65$. The value of .0495 (which rounded off equals .05)

in Column 3 indicates that the proportion of cases in the right tail of the curve that falls above $z = +1.65$ is .0495, and the proportion of cases in the left tail of the curve that falls below $z = -1.65$ is .0495. Note that this is a one-tailed critical value, since the proportion .05 is based on the extreme 5% of the cases in one tail of the distribution.¹¹

The value $z = 2.33$ is referred to as the tabled critical one-tailed .01 z value. This value is employed since the proportion of cases in the normal distribution that falls above $z = +2.33$ or below $z = -2.33$ in each tail of the distribution is .01. This can be confirmed by examining Column 3 of **Table A1** for the value $z = 2.33$. The value of .0099 (which rounded off equals .01) in Column 3 indicates that the proportion of cases in the right tail of the curve that falls above $z = +2.33$ is .0099, and the proportion of cases in the left tail of the curve that falls below $z = -2.33$ is .0099. Note that this is a one-tailed critical value, since the proportion .01 is based on the extreme 1% of the cases in one tail of the distribution.

Although in practice it is not scrupulously adhered to, the conventional hypothesis testing model employed in inferential statistics assumes that prior to conducting a study a researcher stipulates whether a directional or nondirectional alternative hypothesis will be employed, as well as at what level of significance the null hypothesis will be evaluated. The probability value which identifies the level of significance is represented by the notation α , which is the lower case Greek letter **alpha**. Throughout the book the latter value will be referred to as the **prespecified alpha value** (or **prespecified level of significance**), since it will be assumed that the value was specified prior to the data collection phase of a study.

When one employs the term **significance** in the context of scientific research, it is instructive to make a distinction between **statistical significance** and **practical significance**. Statistical significance only implies that the outcome of a study is highly unlikely to have occurred as a result of chance. It does not necessarily suggest that any difference or effect detected in a set of data is of any practical value. As an example, assume that the Scholastic Aptitude Test (SAT) scores of two school districts that employ different teaching methodologies are contrasted. Assume that the teaching methodology of each school district is based on specially designed classrooms. The results of the study indicate that the SAT average in School District A is one point higher than the SAT average in School District B, and this difference is statistically significant at the .01 level. Common sense suggests that it would be illogical for School District B to invest the requisite time and money in order to redesign its physical environment for the purpose of increasing the average SAT score in the district by one point. Thus, in this example, even though the obtained difference is statistically significant, in the final analysis it is of little or no practical significance. The general issue of statistical versus practical significance is discussed in more detail in Section VI of the ***t* test for two independent samples**, and under the discussion of **meta-analysis and related topics** in Section IX (the **Addendum**) of the **Pearson product-moment correlation coefficient (Test 28)**.

Type I and Type II errors in hypothesis testing Within the framework of hypothesis testing, it is possible for a researcher to commit two types of errors. These errors are referred to as a **Type I error** and a **Type II error**.

A **Type I error** is when a true null hypothesis is rejected (i.e., one concludes that a false alternative hypothesis is true). The likelihood of committing a Type I error is specified by the alpha level a researcher employs in evaluating an experiment. The more concerned a researcher is with committing a Type I error, the lower the value of alpha the researcher should employ. Thus, the likelihood of committing a Type I error if $\alpha = .01$, is 1%, as compared with a 5% likelihood if $\alpha = .05$.

A **Type II error** is when a false null hypothesis is retained (i.e., one concludes that a true alternative hypothesis is false). The likelihood of committing a Type II error is represented by

β , which (as noted earlier) is the lower case Greek letter **beta**. The likelihood of rejecting a false null hypothesis represents what is known as the **power** of a statistical test. The power of a test is determined by subtracting the value of beta from 1 (i.e., $\text{Power} = 1 - \beta$). The likelihood of committing a Type II error is inversely related to the likelihood of committing a Type I error. In other words, as the likelihood of committing one type of error decreases, the likelihood of committing the other type of error increases. Thus, with respect to the alternative hypothesis one employs, there is a higher likelihood of committing a Type II error when alpha is set equal to .01 than when it is set equal to .05. The likelihood of committing a Type II error is also inversely related to the power of a statistical test. In other words, as the likelihood of committing a Type II error decreases, the power of the test increases. Consequently, the higher the alpha value (i.e., the higher the likelihood of committing a Type I error), the more powerful the test.

Although the hypothesis testing model as described here is based on conducting a single study in order to evaluate a research hypothesis, throughout the book the author emphasizes the importance of replication in research. This recommendation is based on the fact that inferential statistical tests make certain assumptions, many of which a researcher can never be sure have been met. Since the accuracy of the probability values in tables of critical values for test statistics are contingent upon the validity of the assumptions underlying the test, if any of the assumptions have been violated, the accuracy of the tables can be compromised. In view of this, the most effective way of determining the truth with regard to a particular question, especially if practical decisions are to be made on the basis of the results of research, is to conduct multiple studies which evaluate the same hypothesis. When multiple studies yield consistent results, one is less likely to be challenged that the correct decision has been made with respect to the hypothesis under study. A general discussion of statistical methods that can be employed to aid in the interpretation of the results of multiple studies that evaluate same general hypothesis can be found under the discussion of **meta-analysis and related topics** in Section IX (the **Addendum**) of the **Pearson product-moment correlation coefficient**.

Estimation in Inferential Statistics

In addition to hypothesis testing, inferential statistics can also be employed for estimating the value of one or more population parameters. Within this framework there are two types of estimation. **Point estimation** (which is the less commonly employed of the two methods) involves estimating the value of a parameter from the computed value of a statistic. The more commonly employed method of estimation is **interval estimation**, which involves computing a range of values within which a researcher can state with a high degree of confidence the true value of the parameter falls. Such a range of values is referred to as a **confidence interval**. As an example, a 95% confidence interval for a population mean stipulates the range of values within which a researcher can be 95% confident that the true value of the population mean falls. Stated in probabilistic terms, there is a probability/likelihood of .95 that the true value of the population mean falls within the range of values that define the 95% confidence interval.

Another measure that is often estimated within the framework of research is the **magnitude of treatment effect** (also referred to as **effect size**) present in a study. Effect size is a value that indicates the proportion or percentage of variability on a **dependent variable** that can be attributed to variation on the **independent variable** (the terms **dependent variable** and **independent variable** are defined later in this section). Throughout this book the concept of effect size is discussed, and numerous measures of effect size are presented. At the present time there is considerable debate among researchers with regard to the role that measures of effect size should be accorded in summarizing the results of research. In point of fact, during the past 20 years an increasing number of individuals have become highly critical of the traditional hypothesis testing

model and the associated concept of statistical significance. These individuals have argued that a measure of the effect size computed for a study is more meaningful than whether or not an inferential statistical test has yielded a statistically significant result. The controversy surrounding effect size versus statistical significance is discussed in detail under the discussion of **meta-analysis and related topics** in Section IX (the **Addendum**) of the **Pearson product-moment correlation coefficient**. In addition, it is also addressed within the framework of the discussion of measures of effect size throughout the book (e.g., in Section VI of both the ***t* test for two independent samples** and the **single-factor between-subjects analysis of variance (Test 21)**).

Basic Concepts and Terminology Employed in Experimental Design

Inferential statistical tests can be employed to evaluate data that are generated from a broad range of experimental designs. This section will review some basic terminology in the area of experimental design that will be employed throughout this book.

Typically, experiments involve two or more **experimental conditions**. These conditions are often referred to as **treatments** and, in experiments where different subjects serve in each of the conditions, the term **groups** is commonly employed to differentiate the conditions from one another. At this point it is instructive to review the distinction between a **between-subjects design** and a **within-subjects design**. A **between-subjects design** (also known as an **independent-groups design**) is one in which different subjects serve in each of the experimental conditions. In a **within-subjects design** (also referred to as a **repeated-measures design**, **dependent samples design**, and **correlated samples design**), each subject serves in all of the experimental conditions. A design involving **matched subjects** is also treated as a **within-subjects design**. In a **matched-subjects design** (which is discussed in detail under the ***t* test for two dependent samples (Test 17)**), each subject is paired with one or more other subjects who are similar with respect to one or more characteristics that are highly correlated with the dependent variable (which will be discussed shortly). A **matched-subjects design** and a **within-subjects design** are sometimes categorized as a **randomized-blocks design**. The latter term refers to a design that employs homogeneous blocks of subjects (which matched subjects represent). When a **within-subjects design** is conceptualized as a **randomized-blocks design**, it is because within each block the same subject is matched with himself by virtue of serving under all of the experimental conditions.

A basic distinction in experimental design is that made between an **independent** and a **dependent variable**. In any experiment involving two or more experimental conditions, the **independent variable** is the experimental manipulation or preexisting subject characteristic that distinguishes the different experimental conditions from one another. Thus, in the antidepressant drug study discussed earlier, the independent variable is whether or not a subject receives a drug or a placebo. Since the number of **levels** of an independent variable corresponds to the number of experimental conditions or treatments, the independent variable in the drug study is comprised of two levels.

A **dependent variable** is the specific measure which is hypothesized to be influenced by or associated with the independent variable. Thus in the drug study, the depression scores of subjects represent the dependent variable, since it is hypothesized that the depression score of a subject will be a function of which treatment the subject receives. When a null hypothesis is rejected in an experiment involving two or more treatments, the researcher is concluding that the subjects' scores on the dependent variable are dependent upon which level of the independent variable they were assigned.

It is possible to have more than one independent variable in an experiment. Experimental

designs that involve more than one independent variable are referred to as **factorial designs**. In such experiments, the number of independent variables will correspond to the number of factors in the experiment, and each independent variable/factor will be comprised of two or more levels. It is also possible to have more than two dependent variables in an experiment. Typically, experiments involving two or more dependent variables are evaluated with **multivariate statistical procedures**, a topic that will not be covered in detail in this book.

In describing a **between-subjects design**, a distinction is commonly made between a **true experiment** as opposed to a **natural experiment** (which is also referred to as an **ex post facto study**). This distinction is predicated on the fact that in a **true experiment** the following applies: a) Subjects are **randomly assigned** to a group; and b) The independent variable is **manipulated** by the experimenter. The antidepressant drug study illustrates an example of an experiment in which the independent variable is manipulated, since in that study the experimenter determined who received the drug and who received the placebo. In a **natural experiment** random assignment of subjects to groups is impossible, since the independent variable is not manipulated by the experimenter, but instead is some preexisting subject characteristic (such as gender, race, etc.). Thus, if we compare the overall health of smokers and nonsmokers, the independent variable in such a study is whether or not a person smokes, which is something that is determined by "nature" prior to the experiment.

The advantage of a **true experiment** over a **natural experiment** is that the **true experiment** allows a researcher to exercise much greater control over the experimental situation. Since the experimenter randomly assigns subjects to groups in the **true experiment**, it is assumed that the groups formed are equivalent to one another, and as a result of this any differences between the groups with respect to the dependent variable can be directly attributed to the manipulated independent variable. The end result of all this is that the **true experiment** allows a researcher to draw conclusions with regard to cause and effect.

The **natural experiment**, on the other hand, does not allow one to draw conclusions with regard to cause and effect. Essentially the type of information that results from a **natural experiment** is **correlational** in nature. Such experiments can only tell a researcher that a statistical association exists between the independent and dependent variables. The reason why **natural experiments** do not allow a researcher to draw conclusions with regard to cause and effect is that such experiments do not control the potential effects of **confounding variables** (also known as **extraneous variables**). A **confounding variable** is any variable that systematically varies with the different levels of the independent variable. To illustrate, assume that in a study comparing the overall health of smokers and nonsmokers, unbeknownst to the researcher all of the smokers in the study are people who have high stress jobs and all the nonsmokers are people with low stress jobs. If the outcome of such a study indicates that smokers are in poorer health than nonsmokers, the researcher will have no way of knowing whether the inferior health of the smokers is due to smoking and/or job stress, or even to some other confounding variable of which he is unaware.

Correlational Research

As noted above, **natural experiments** only provide correlational information. In point of fact, there are a large number of correlational measures that have been developed which are appropriate for use with different kinds of data. Measures of correlation are not inferential statistical tests, but are instead, descriptive measures which indicate the degree to which two or more variables are related to one another. Upon computing a measure of correlation, it is common practice to employ one or more inferential statistical tests to evaluate one or more hypotheses concerning the degree to which the variables are related to one another. Although correlations

can be computed for more than two variables, the primary focus in this book will be on **bivariate correlational procedures**, which are procedures that measure the degree of association between two variables.

In the typical correlational study, scores on two measures/variables are available for n subjects. A major goal of correlational research is to determine the degree to which a subject's score on one variable can be predicted, if one knows the score of the subject on the second variable. As a general rule (although there are exceptions), the value computed for a measure of correlation/association (often referred to as a **correlation coefficient**) will usually fall within a range of values between 0 and an absolute value of 1. Whereas a value of 0 indicates that no statistical relationship exists between the variables, an absolute value of 1 indicates the presence of a maximal relationship. Consequently, the closer the absolute value of a correlation is to 1, the stronger the relationship between the two variables. To state it another way, the closer the absolute value of a correlation is to 1, the more accurately a subject's score on one variable can be predicted from the subject's score on the second variable.

Many measures of correlation can assume both positive and negative values, and, typically, in such cases, the range of values the coefficient of correlation can assume is between -1 and $+1$. Whereas the absolute value of a correlation coefficient indicates the strength of the relationship between the two variables, the sign of the correlation coefficient indicates the nature of the relationship. A positive correlation indicates the presence of what is referred to as a **direct relationship**. In a **direct relationship** a change in one variable is associated with a change in the other variable in the **same direction**. On the other hand, a negative correlation indicates the presence of an **indirect** or **inverse relationship** between the variables. In an **indirect relationship** a change in one variable is associated with a change in the other variable in the **opposite direction**. A more comprehensive discussion of the subject of correlation can be found in Section I of the **Pearson product-moment correlation coefficient**.

Parametric versus Nonparametric Inferential Statistical Tests

The inferential statistical procedures discussed in this book have been categorized as being **parametric** versus **nonparametric tests**. Some sources distinguish between parametric and nonparametric tests on the basis that **parametric tests** make specific assumptions with regard to one or more of the population parameters that characterize the underlying distribution(s) for which the test is employed. These same sources describe **nonparametric tests** as making no such assumptions about population parameters. In truth, nonparametric tests are really not assumption free, and in view of this some sources (e.g., Marascuilo and McSweeney (1977)) suggest that it might be more appropriate to employ the term "**assumption freer**" rather than nonparametric in relation to such tests.

The distinction employed in this book for categorizing a procedure as a parametric versus a nonparametric test is primarily based on the level of measurement represented by the data that are being analyzed. As a general rule, inferential statistical tests that evaluate **categorical/nominal data** and **ordinal/rank-order data** are categorized as **nonparametric tests**, while those tests that evaluate **interval data** or **ratio data** are categorized as **parametric tests**. Although the appropriateness of employing level of measurement as a criterion in this context has been debated, its usage provides a reasonably simple and straightforward schema for categorization that facilitates the decision-making process for selecting an appropriate statistical test.

There is general agreement among most researchers that as long as there is no reason to believe that one or more of the assumptions of a parametric test have been violated, when the level of measurement for a set of data is interval or ratio, the data should be evaluated with the appropriate parametric test. However, if one or more of the assumptions of a parametric test are

violated, some (but not all) sources believe it is prudent to transform the data into a format that makes it compatible for analysis with the appropriate nonparametric test. Related to this is that even though parametric tests generally provide a more powerful test of an alternative hypothesis than their nonparametric analogs, the power advantage of a parametric test may be negated if one or more of its assumptions are violated.

The reluctance among some sources to transform interval/ratio data¹² into an ordinal/rank-order or categorical/nominal format for the purpose of analyzing it with a nonparametric test, is based on the fact that interval/ratio data contain more information than either of the latter two forms of data. Because of their reluctance to sacrifice information, these sources take the position that even when there is reason to believe that one or more of the assumptions of a parametric test has been violated, it is still more prudent to employ the appropriate parametric test. Generally, when a parametric test is employed under such conditions, certain adjustments are made in evaluating the test statistic in order to improve its reliability.

In the final analysis, the debate concerning whether one should employ a parametric or nonparametric test for a specific experimental design turns out to be of little consequence in most instances. The reason for this is that most of the time a parametric test and its nonparametric analog are employed to evaluate the same set of data, they lead to identical or similar conclusions. This latter observation is demonstrated throughout this book with numerous examples. In those instances where the two types of test yield conflicting results, the truth can best be determined by conducting multiple experiments which evaluate the hypothesis under study. A detailed discussion of statistical methods that can be employed for pooling the results of multiple studies that evaluate the same general hypothesis can be found under the discussion of **meta-analysis and related topics** in Section IX (the **Addendum**) of the **Pearson product-moment correlation coefficient**.

Selection of the Appropriate Statistical Procedure

The Handbook of Parametric and Nonparametric Statistical Procedures is intended to be a comprehensive resource on inferential statistical tests and measures of correlation/association. The section to follow presents an outline of the statistical procedures covered in the book. Following the outline the reader is provided with guidelines and accompanying decision tables to facilitate the selection of the appropriate statistical procedure for a specific experimental design.

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Endnotes

1. Strictly speaking \tilde{s} is not an unbiased estimate of σ , although it is usually employed as such. In point of fact, \tilde{s} slightly underestimates σ , especially when the value of n is small. Zar (1999) notes that although corrections for bias in estimating σ have been developed by Gurland and Tripathi (1971) and Tolman (1971), they are rarely employed, since they generally have no practical impact on the outcome of an analysis.
2. The inequality sign $>$ means **greater than**. Some other inequality signs used throughout the book are $<$, which means **less than**; \geq , which means **greater than or equal to**; and \leq , which means **less than or equal to**.
3. The **absolute value** is the magnitude of a number irrespective of the sign.
4. McElroy (1979) describes the use of the equation $skewness = (\bar{X} - M)/\tilde{s}$ as an alternative approximate measure of skewness. McElroy (1979) and Zar (1999) describe the following measure of skewness, referred to as the **Bowley coefficient of skewness** (Bowley (1920)), which employs quartiles of the distribution (where Q_i represents the i^{th} quartile): $Skewness = (Q_3 + Q_1 - 2Q_2)/(Q_3 - Q_1)$. The latter index yields values in the range -1 for a maximally negatively skewed distribution to $+1$ for a maximally positively skewed distribution.
5. The symbol π in Equations I.25 and I.26 represents the mathematical constant **pi** (which equals 3.14159...). The numerical value of π represents the ratio of the circumference of a circle to its diameter. The value e in Equations I.25 and I.26 equals 2.71828... . Like π , e is a fundamental mathematical constant. Specifically, e is the base of the natural system of logarithms, which will be clarified shortly. Both π and e represent what are referred to as **irrational numbers**. An **irrational number** has a decimal notation that goes on forever without a repeating pattern of digits. In contrast, a **rational number** (derived from the word ratio) is either an integer or a fraction (which is the ratio between whole/integer numbers), which when expressed as a decimal always terminates at some point or assumes a repetitive pattern. Examples of rational numbers are $1/4 = .25$ which has a terminating decimal, or $1/3 = .33333...$, which is characterized by an endless repeating pattern of digits (Hoffman, 1998).

A **logarithm** is the value of an exponent which indicates the power that a number, which is referred to as a **base value**, must be raised in order to yield a specific number

value. Typically, e and the number 10 are employed as base values for logarithms. Logarithms that employ e as the base value are referred to as **natural** (or **Naperian**) logarithms, while logarithms that employ 10 as the base value are referred to as **common** (or **Briggsian**) logarithms. The notation $\log_e 20 = 2.9957$ or $\ln 20 = 2.9957$ indicates that the value of e (which is the base value of the logarithm) must be raised to the 2.9957th power in order to result in the value 20. Note that if the notation \log is employed when e is the base value, the subscript e must be indicated, whereas if the notation \ln is employed, it is assumed that e is the base value of the logarithm. If the notation $\log 20$ is employed without the e subscript, it is assumed that the base of the logarithm is 10. Thus, $\log 20 = 1.3010$, indicates that 10 must be raised to the 1.3010th power to equal 20. Logarithms are employed later in the book within the framework of the operations involved in a number of statistical procedures.

6. Previously, the term **tail** was defined as the lower or upper extremes of a distribution. Although the latter definition is correct, I am taking some liberty here by employing the term **tail** in this context to refer more generally to the left or right half of the distribution.
7. Although the values in **Column 4** of **Table A1** will not be employed in our example, a brief explanation of what they represent follows. In the case of the standard normal distribution, when a value of X is substituted in Equations I.25 or I.26, the value of X will correspond to a z score. When a z value is employed to represent X , the value of Y computed with Equation I.25/I.26 will correspond to the value recorded for the **ordinate** in **Column 4** of **Table A1**. The value of the ordinate represents the height of the normal curve for that z value. To illustrate, if the value $z = 0$ is employed to represent X , Equation I.25/I.26 reduces to $Y = 1/\sqrt{2\pi}$, which equals $Y = 1/\sqrt{(2)(3.1416)} = .3989$. The resulting value .3989 is the value recorded in **Column 4** of **Table A1** for the ordinate that corresponds to the z score $z = 0$.
8. A proportion is converted into a percentage by moving the decimal point two places to the right.
9. In actuality, the values of the sample means do not have to be identical to support the null hypothesis. Due to **sampling error**, which is a discrepancy between the value of a statistic and the parameter it estimates, even when two samples come from the same population, the value of the two sample means will usually not be identical. The larger the sample size employed in a study, the less the influence of sampling error and, consequently, the closer one can expect two sample means to be to one another if, in fact, they do represent the same population. With small sample sizes, however, a large difference between sample means is not unusual even when the samples come from the same population and, because of this, a large difference may not be grounds for rejecting the null hypothesis.
10. Some sources employ the notation $p \leq .05$, indicating a probability of equal to or less than .05. The latter notation will not be used unless the computed value of a test statistic is the exact value of the tabled critical value.
11. Inspection of **Column 3** in **Table A1** reveals that the proportion for $z = 1.64$ is .0505. This latter value is the same distance from the proportion .05 as the value .0495 derived for $z = 1.65$. If **Table A1** documented proportions to five decimal places, it would turn out that z

$= 1.65$ yields a value that is slightly closer to .05 than does $z = 1.64$. Some books, however, do employ $z = 1.64$ as the tabled critical one-tailed .05 z value.

12. Since interval and ratio data are viewed the same within the decision making process with respect to test selection, the expression interval/ratio will be used throughout to indicate that either type of data is appropriate for use with a specific test.

Outline of Inferential Statistical Tests and Measures of Correlation/Association

I. Inferential statistical tests employed with a single sample

- A. Inferential statistical tests employed with interval/ratio data
 - 1. Inferential statistical tests employed with interval/ratio data for evaluating a hypothesis about the mean of a single population
 - Test 1: The Single-Sample z Test**
 - Test 2: The Single-Sample t Test**
 - 2. Inferential statistical tests employed with interval/ratio data for evaluating a hypothesis about a population parameter/characteristic other than a mean
 - Test 3: The Single-Sample Chi-Square Test for a Population Variance**
 - Test 4: The Single-Sample Test for Evaluating Population Skewness**
 - Test 5: The Single-Sample Test for Evaluating Population Kurtosis**
 - Test 5a: The D'Agostino–Pearson Test of Normality**
 - Test 10f: The Mean Square Successive Difference Test (for serial randomness)**
 - Test 11e: Procedures for Identifying Outliers**
- B. Inferential statistical tests employed with ordinal/rank-order data
 - 1. Inferential statistical tests employed with ordinal/rank-order data for evaluating a hypothesis about the median of a single population, or the distribution of data in a single population
 - Test 6: The Wilcoxon Signed-Ranks Test**
 - Test 7: The Kolmogorov–Smirnov Goodness-of-fit Test for a Single Sample**
 - Test 7a: The Lilliefors Test for Normality**
 - Test 9b: The Single-Sample Test for the Median**
- C. Inferential statistical tests employed with categorical/nominal data
 - 1. Inferential statistical tests employed with categorical/nominal data for evaluating a hypothesis about the distribution of data in a single population
 - Test 8: The Chi-Square Goodness-of-Fit Test**
 - Test 9: The Binomial Sign Test for a Single Sample**
 - Test 9a: The z Test for a Population Proportion**
 - Test 10: The Single-Sample Runs Test**
 - Test 10a: The Runs Test for Serial Randomness**
 - Test 10b: The Frequency Test (for Randomness)**
 - Test 10c: The Gap Test (for Randomness)**
 - Test 10d: The Poker Test (for Randomness)**
 - Test 10e: The Maximum Test (for Randomness)**
 - Test 16b: The Chi-Square Test of Independence**

II. Inferential statistical tests employed with two independent samples

- A. Inferential statistical tests employed with interval/ratio data
 - 1. Inferential statistical tests employed with interval/ratio data for evaluating a hypothesis about the means of two independent populations

- Test 11: **The t Test for Two Independent Samples**
 - Test 11d: **The z Test for Two Independent Samples**
 - Test 21: **The Single-Factor Between-Subjects Analysis of Variance**
 - Test 21j: **The Single-Factor Between-Subjects Analysis of Covariance**
- 2. Inferential statistical tests employed with interval/ratio data for evaluating a hypothesis about variability in two independent populations
 - Test 11a: **Hartley's F_{\max} Test for Homogeneity of Variance/ F Test for Two Population Variances**
- B. Inferential statistical tests employed with ordinal/rank-order data
 - 1. Inferential statistical tests employed with ordinal/rank-order data for evaluating a hypothesis about the medians, or some other characteristic (other than variability) of two independent populations
 - Test 12: **The Mann–Whitney U Test**
 - Test 12a: **The Randomization Test for Two Independent Samples**
 - Test 12b: **The Bootstrap (can be employed for variability)**
 - Test 12c: **The Jackknife (can be employed for variability)**
 - Test 13: **The Kolmogorov–Smirnov Test for Two Independent Samples**
 - Test 16e: **The Median Test for Independent Samples**
 - Test 23: **The van der Waerden Normal-Scores Test for k Independent Samples**
 - 2. Inferential statistical tests employed with ordinal/rank-order data for evaluating a hypothesis about variability of two independent populations
 - Test 14: **The Siegel–Tukey Test for Equal Variability**
 - Test 15: **The Moses Test for Equal Variability**
- C. Inferential statistical tests employed with categorical/nominal data
 - 1. Inferential statistical tests employed with categorical/nominal data for evaluating a hypothesis about the distribution of data in two independent populations
 - Test 16a: **The Chi-Square Test for Homogeneity**
 - Test 16c: **The Fisher Exact Test**
 - Test 16d: **The z Test for Two Independent Proportions**

III. Inferential statistical tests employed with two dependent samples

- A. Inferential statistical tests employed with interval/ratio data
 - 1. Inferential statistical tests employed with interval/ratio data for evaluating a hypothesis about the means of two dependent populations
 - Test 17: **The t Test for Two Dependent Samples**
 - Test 17d: **Sandler's A Test**
 - Test 17e: **The z Test for Two Dependent Samples**
 - Test 24: **The Single-Factor Within-Subjects Analysis of Variance**
 - 2. Inferential statistical tests employed with interval/ratio data for evaluating a hypothesis about variability in two dependent populations
 - Test 17a: **The t Test for Homogeneity of Variance for Two Dependent Samples**
- B. Inferential statistical tests employed with ordinal/rank-order data
 - 1. Inferential statistical tests employed with ordinal/rank-order data for evaluating a hypothesis about the ordering of data in two dependent populations
 - Test 18: **The Wilcoxon Matched-Pairs Signed-Ranks Test**
 - Test 19: **The Binomial Sign Test for Two Dependent Samples**
- C. Inferential statistical tests employed with categorical/nominal data

1. Inferential statistical tests employed with categorical/nominal data for evaluating a hypothesis about the distribution of data in two dependent populations

Test 20: The McNemar Test

Test 20a: The Bowker Test of Symmetry

IV. Inferential statistical tests employed with two or more independent samples

A. Inferential statistical tests employed with interval/ratio data

1. Inferential statistical tests employed with interval/ratio data for evaluating a hypothesis about the means of two or more independent populations which involve one independent variable/factor

Test 21: The Single-Factor Between-Subjects Analysis of Variance

Test 21a: Multiple t Tests/Fisher's LSD Test

Test 21b: The Bonferroni–Dunn test

Test 21c: Tukey's HSD Test

Test 21d: The Newman–Keuls Test

Test 21e: The Scheffé Test

Test 21f: The Dunnett Test

Test 21j: The Single-Factor Between-Subjects Analysis of Covariance

2. Inferential statistical tests employed with interval/ratio data for evaluating a hypothesis about variability in two or more independent populations

Test 11a: Hartley's F_{\max} Test for Homogeneity of Variance/ F Test for Two Population Variances

B. Inferential statistical tests employed with ordinal/rank-order data

1. Inferential statistical tests employed with ordinal/rank data for evaluating a hypothesis about the medians, or some other characteristic of two or more independent populations

Test 16e: The Median Test for Independent Samples

Test 22: The Kruskal–Wallis One-Way Analysis of Variance by Ranks

Test 23: The van der Waerden Normal-Scores Test for k Independent Samples

C. Inferential statistical tests employed with categorical/nominal data

1. Inferential statistical tests employed with categorical/nominal data for evaluating a hypothesis about the distribution of data in two or more independent populations

Test 16a: The Chi-Square Test for Homogeneity

V. Inferential statistical tests employed with two or more dependent samples

A. Inferential statistical tests employed with interval/ratio data

1. Inferential statistical tests employed with interval/ratio data for evaluating a hypothesis about the means of two or more dependent populations which involve one independent variable/factor.

Test 24: The Single-Factor Within-Subjects Analysis of Variance

Test 24a: Multiple t Tests/Fisher's LSD Test

Test 24b: The Bonferroni–Dunn Test

Test 24c: Tukey's HSD Test

Test 24d: The Newman–Keuls Test

Test 24e: The Scheffé Test

Test 24f: The Dunnett Test

B. Inferential statistical tests employed with ordinal/rank-order data

1. Inferential statistical tests employed with ordinal/rank-order data for evaluating

a hypothesis about the medians of two or more dependent populations

Test 25: The Friedman Two-Way Analysis of Variance by Ranks

- C. Inferential statistical tests employed with categorical/nominal data
 - 1. Inferential statistical tests employed with categorical/nominal data for evaluating a hypothesis about the distribution of data in two or more dependent populations

Test 26: The Cochran Q Test

VI. Inferential statistical tests employed with factorial designs

- A. Inferential statistical tests employed with interval/ratio data
 - 1. Inferential statistical tests employed with interval/ratio data for evaluating a hypothesis about the means of two or more populations in a design involving two independent variables/factors

Test 27: The Between-Subjects Factorial Analysis of Variance

Test 27a: Multiple t Tests/Fisher's LSD Test

Test 27b: The Bonferroni–Dunn Test

Test 27c: Tukey's HSD Test

Test 27d: The Newman–Keuls Test

Test 27e: The Scheffé Test

Test 27f: The Dunnett Test

Test 27i: The Factorial Analysis of Variance for a Mixed Design

Test 27j: The Within-Subjects Factorial Analysis of Variance

VII. Measures of correlation/association

- A. Measures of correlation/association employed with interval/ratio data
 - 1. Bivariate measures
 - Test 28: The Pearson Product–Moment Correlation Coefficient** (and tests for evaluating various hypotheses concerning the value of one or more product-moment correlation coefficients or regression coefficients (**Tests 28a–28g**))
 - 2. Multivariate measures
 - Test 28k: The Multiple Correlation Coefficient** (and the test for evaluating the significance of a multiple correlation coefficient (**Test 28k-a**))
 - Test 28l: The Partial Correlation Coefficient** (and the test for evaluating the significance of a partial correlation coefficient (**Test 28l-a**))
 - Test 28m: The Semipartial Correlation Coefficient** (and the test for evaluating the significance of a semi-partial correlation coefficient (**Test 28m-a**))
- B. Measures of correlation/association employed with ordinal/rank order data
 - 1. Bivariate measures/Two sets of ranks
 - Test 29: Spearman's Rank-Order Correlation Coefficient** (and the test for evaluating the significance of Spearman's rank-order correlation coefficient (**Test 29a**))
 - Test 30: Kendall's Tau** (and the test for evaluating the significance of Kendall's tau (**Test 30a**))
 - Test 32: Goodman and Kruskal's Gamma** (and the test for evaluating the significance of gamma (**Test 32a**))
 - 2. Ordinal measure of association for three or more samples/sets of ranks
 - Test 31: Kendall's Coefficient of Concordance** (and the test for evaluating the significance of the coefficient of concordance (**Test 31a**))

- C. Measures of correlation/association employed with categorical/nominal data
 - Test 16f: **The Contingency Coefficient**
 - Test 16g: **The Phi Coefficient**
 - Test 16h: **Cramér's Phi Coefficient**
 - Test 16i: **Yule's Q**
 - Test 16j: **The Odds Ratio** (and test of significance for an odds ratio (**Test 16j-a**))
- D. Other bivariate measures of correlation/association (and effect size) employed when interval/ratio data are used or implied for at least one variable
 - Test 28h: **The Point-Biserial Correlation Coefficient** (and the test for evaluating the significance of a point-biserial correlation coefficient (**Test 28h-a**))
 - Test 28i: **The Biserial Correlation Coefficient** (and the test for evaluating the significance of a biserial correlation coefficient (**Test 28i-a**))
 - Test 28j: **The Tetrachoric Correlation Coefficient** (and the test for evaluating the significance of a tetrachoric correlation coefficient (**Test 28j-a**))
 - Tests 11c/17c/21g/24g/27g: **Omega Squared**
 - Test 21h: **Eta Squared**
 - Test 11b/17b: **Cohen's d Index** (and **Test 2a** for one variable)
 - Test 21i/24h/27h: **Cohen's f Index**

VIII. Additional procedures

- A. Meta-analytic procedures
 - Test 28n: **Procedure for comparing k studies with respect to significance level**
 - Test 28o: **The Stouffer procedure for obtaining a combined significance level for k studies**
 - Test 28p: **Procedure for comparing k studies with respect to effect size**
 - Test 28q: **Procedure for obtaining a combined effect size for k studies**

Guidelines and Decision Tables for Selecting the Appropriate Statistical Procedure

Tables I.8–I.11 are designed to facilitate the selection of the appropriate statistical test. Tables I.8–I.10 list the major inferential statistical procedures described in the book, based on the level of measurement the data being evaluated represent. Specifically, Table I.8 lists inferential statistical tests employed with interval/ratio data, Table I.9 lists inferential statistical tests employed with ordinal/rank-order data,* and Table I.10 lists inferential statistical tests employed with categorical/nominal data. Table I.11 lists the measures of correlation/association that are described in the book. Using the aforementioned tables, the following guidelines should be employed in selecting the appropriate statistical test.

1. Determine if the analysis involves computing a correlation coefficient/measure of association and, if it does, go to Table I.11. The selection of the appropriate measure in Table I.11 is based on the level of measurement represented by each of the variables for which the measure of correlation/association is computed.
2. If the analysis does not involve computing a measure of correlation/association, it will be assumed that the data will be evaluated through use of an inferential statistical test. To select the appropriate inferential statistical test, the following protocol should be employed.
 - a) State the general hypothesis that is being evaluated.
 - b) Determine if the study involves a single sample or more than one sample.
 - c) If the study involves a single sample, the appropriate test will be one of the tests for a single sample in Tables I.8, I.9, or I.10. In order to determine which table to employ, determine the level of measurement represented by the data that are being evaluated. If the level of measurement is interval/ratio, Table I.8 is employed. If the level of measurement is ordinal/rank-order, Table I.9 is appropriate. If the level of measurement is categorical/nominal, Table I.10 is utilized.
 - d) If there is more than one sample, determine how many samples/treatments there are and whether they are independent or dependent. Determine the level of measurement represented by the data that are being evaluated (which represents the dependent variable in the study).
 - 1) If the level of measurement is interval/ratio, go to Table I.8. Identify the test or tests that are appropriate for that level of measurement with respect to the number and type of samples employed in the study.
 - 2) If the level of measurement is ordinal/rank-order, go to Table I.9. Identify the test or tests that are appropriate for that level of measurement with respect to the number and type of samples employed in the study.
 - 3) If the level of measurement is categorical/nominal, go to Table I.10. Identify the test or tests that are appropriate for that level of measurement with respect to the number and type of samples employed in the study.

* In the case of the following three tests listed in Table I.9, the dependent variable will be interval/ratio data which is converted into a format in which the resulting scores are rank-ordered: The **Wilcoxon signed-ranks test (Test 6)**, the **Moses test for equal variability (Test 15)**, and the **Wilcoxon matched-pairs signed-ranks test (Test 18)**.

Table I.8 Decision Table for Inferential Statistical Tests Employed with Interval/Ratio Data

Number of samples		Hypothesis evaluated	Test
One independent variable			
Single sample		Hypothesis about a population mean	The single-sample z test (Test 1) (σ known) The single-sample t test (Test 2) (σ unknown)
		Hypothesis about a population parameter/characteristic other than the mean	The single-sample chi-square test for a population variance (Test 3) The single-sample test for evaluating population skewness (Test 4) The single-sample test for evaluating population kurtosis (Test 5) The mean square successive difference test (for serial randomness) (Test 10f) The D'Agostino–Pearson test of normality (Test 5a) Procedures for identifying outliers (Test 11e)
Two samples	Two independent samples	Hypothesis about difference between two independent population means	The t test for two independent samples (Test 11) The z test for two independent samples (Test 11d) The single-factor between-subjects analysis of (Test 21) The single-factor between-subjects analysis of covariance (Test 21j)
		Hypothesis about two independent population variances	Hartley's F_{\max} test for homogeneity of variance/ F test for two population variances (Test 11a)
	Two dependent samples	Hypothesis about difference between two dependent population means	The t test for two dependent samples (Test 17) Sandler's A test (Test 17d) The z test for two dependent samples (Test 17e) The single-factor within-subjects analysis of variance (Test 24)
		Hypothesis about two dependent population variances	The t test for homogeneity of variance for two dependent samples (Test 17a)
Two or more samples	Two or more independent samples	Hypothesis about difference between two or more independent population means	The single-factor between-subjects analysis of variance (Test 21) The single-factor between-subjects analysis of covariance (Test 21j)
		Hypothesis about two or more independent population variances	Hartley's F_{\max} test for homogeneity of variance/ F test for two population variances (Test 11a)
	Two or more dependent samples	Hypothesis about difference between two or more dependent population means	The single-factor within-subjects analysis of variance (Test 24)
		Hypothesis about two or more dependent population variances	See discussion of sphericity assumption under the single-factor within-subjects analysis of variance (Test 24)
Two independent variables		Hypothesis about difference between two or more population means	The between-subjects factorial analysis of variance (Test 27) The factorial analysis of variance for a mixed design (Test 27i) The within-subjects factorial analysis of variance (Test 27j)

**Table I.9 Decision Table for Inferential Statistical Tests Employed
with Ordinal/Rank-Order Data**

Number of samples		Hypothesis evaluated	Test
Single sample		Hypothesis about a population median or the distribution of data in a single population	The Wilcoxon signed-ranks test (Test 6) The Kolmogorov–Smirnov goodness-of-fit test for a single sample (Test 7) The Lilliefors test for normality (Test 7a) The single-sample test for the median (Test 9b)
Two samples	Two independent samples	Hypothesis about two independent population medians, or some other characteristic (other than variability) of two independent populations	The Mann–Whitney U test (Test 12) The randomization test for two independent samples (Test 12a) The bootstrap (Test 12b) (can be employed for variability) The jackknife (Test 12b) (can be employed for variability) The Kolmogorov–Smirnov test for two independent samples (Test 13) The median test for independent samples (Test 16e) The van der Waerden normal-scores test for k independent samples (Test 23)
		Hypothesis about variability in two independent populations	The Siegel–Tukey test for equal variability (Test 14) The Moses test for equal variability (Test 15)
	Two dependent samples	Hypothesis about the ordering of data in two dependent populations	The Wilcoxon matched-pairs signed-ranks test (Test 18) The binomial sign test for two dependent samples (Test 19)
Two or more samples	Two or more independent samples	Hypothesis about two or more independent population medians, or some other characteristic of two or more independent populations	The Kruskal–Wallis one-way analysis of variance by ranks (Test 22) The van der Waerden normal-scores test for k independent samples (Test 23) The median test for independent samples (Test 16e)
	Two or more dependent samples	Hypothesis about two or more dependent population medians	The Friedman two-way analysis of variance by ranks (Test 25)

**Table I.10 Decision Table for Inferential Statistical Tests Employed
with Categorical/Nominal Data**

Number of samples		Hypothesis evaluated	Test
Single sample		Hypothesis about distribution of data in a single population	The chi-square goodness-of-fit test (Test 8) The binomial sign test for a single sample (Test 9) The z test for a population proportion (Test 9a) The single-sample runs test (Test 10) The runs test for serial randomness (Test 10a) The frequency test (for randomness) (Test 10b) The gap test (for randomness) (Test 10c) The poker test (for randomness) (Test 10d) The maximum test (for randomness) (Test 10e) The chi-square test of independence (Test 16b)
Two samples	Two independent samples	Hypothesis about distribution of data in two independent populations	The chi-square test for homogeneity (Test 16a) The Fisher exact test (Test 16c) The z test for two independent proportions (Test 16d)
	Two dependent samples	Hypothesis about distribution of data in two dependent populations	The McNemar test (Test 20) The Bowker test of symmetry (Test 20a)
Two or more samples	Two or more independent samples	Hypothesis about distribution of data in two or more independent populations	The chi-square test for homogeneity (Test 16a)
	Two or more dependent samples	Hypothesis about distribution of data in two or more dependent populations	The Cochran Q test (Test 26)

Table I.11 Decision Table for Measures of Correlation/Association

Level of measurement		Test
Interval/ratio data	Bivariate	The Pearson product-moment correlation coefficient (Test 28)
	Multivariate	The multiple correlation coefficient (Test 28k) The partial correlation coefficient (Test 28l) The semipartial correlation coefficient (Test 28m)
Ordinal/rank order data	Bivariate/two sets of ranks	Spearman's rank-order correlation coefficient (Test 29) Kendall's tau (Test 30) Goodman and Kruskal's gamma (for ordered contingency tables) (Test 32)
	More than two samples/sets of ranks	Kendall's coefficient of concordance (Test 31)
Categorical/nominal data	Two dichotomous variables	The contingency coefficient (Test 16f) The phi coefficient (Test 16g) Yule's Q (Test 16i) The odds ratio (Test 16j)
	Two nondichotomous variables	The contingency coefficient (Test 16f) Cramér's phi coefficient (Test 16h) The odds ratio (Test 16j)
Other bivariate correlational measures for which interval ratio/data are employed or implied for at least one of the variables		Omega squared (One variable, interval/ratio data; second variable, two or more nominal levels) (Tests 11c/17c/21g/24g/27g) Eta squared (One variable, interval/ratio data; second variable, two or more nominal levels) (Test 21h) Cohen's d index (Test 11b/17b) (One variable, interval/ratio data; second variable, two nominal levels) (with Test 2a for one variable) Cohen's f index (One variable, interval/ratio data; second variable, two or more nominal levels) (Test 21i/24h/27h) The point-biserial correlation coefficient (One variable, interval/ratio data; second variable represented by dichotomous categories) (Test 28h) The biserial correlation coefficient (One variable, interval/ratio data; second variable, an interval/ratio variable expressed in form of dichotomous categories) (Test 28i) The tetrachoric correlation coefficient (Two interval/ratio variables, both of which are expressed in the the form of dichotomous categories) (Test 28j)

Inferential Statistical Tests Employed with a Single Sample

- Test 1: The Single-Sample z Test**
- Test 2: The Single-Sample t Test**
- Test 3: The Single-Sample Chi-Square Test for
a Population Variance**
- Test 4: The Single-Sample Test for Evaluating
Population Skewness**
- Test 5: The Single-Sample Test for Evaluating
Population Kurtosis**
- Test 6: The Wilcoxon Signed-Ranks Test**
- Test 7: The Kolmogorov-Smirnov Goodness-of-Fit
Test for a Single Sample**
- Test 8: The Chi-Square Goodness-of-Fit Test**
- Test 9: The Binomial Sign Test for a Single Sample**
- Test 10: The Single-Sample Runs Test (and Other
Tests of Randomness)**

Test 1

The Single-Sample z Test (Parametric Test Employed with Interval/Ratio Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test Does a sample of n subjects (or objects) come from a population in which the mean (μ) equals a specified value?

Relevant background information on test The **single-sample z test** is employed in a hypothesis testing situation involving a single sample in order to determine whether or not a sample with a mean of \bar{X} is derived from a population with a mean of μ . If the result of the **single-sample z test** yields a significant difference, the researcher can conclude there is a high likelihood the sample is derived from a population with a mean value other than μ . The test statistic for the **single-sample z test** is based on the normal distribution. A general discussion of the normal distribution can be found in the **Introduction**.

The **single-sample z test** is used with interval/ratio data. The test should only be employed if the value of the population standard deviation (σ) is known. In the event the value of σ is unknown, the data should be evaluated with the **single-sample t test (Test 2)**. The reader should take note of the fact that some sources argue that even when one knows the value of σ , if the sample size is very small, the **single-sample t test** provides a more accurate estimate of the underlying sampling distribution for the data. Sources that take the latter position are not in agreement with respect to the minimum sample size above which it is acceptable to employ the **single-sample z test** (although it is usually $n \geq 25$).

The **single-sample z test** is based on the following assumptions: a) The sample has been randomly selected from the population it represents; and b) The distribution of data in the underlying population the sample represents is normal. If either of the aforementioned assumptions is saliently violated, the reliability of the z test statistic may be compromised.

II. Example

Example 1.1. *Thirty subjects take a test of visual-motor coordination for which the value of the population mean is $\mu = 8$, and the value of the population standard deviation is $\sigma = 2$. If the average score of the sample of 30 subjects equals 7.4 (i.e., $\bar{X} = 7.4$), can one conclude that the sample, in fact, came from a population in which the mean is $\mu = 8$?*

III. Null versus Alternative Hypotheses

Null hypothesis

$$H_0: \mu = 8$$

(The mean of the population the sample represents equals 8.)

Alternative hypothesis

$$H_1: \mu \neq 8$$

(The mean of the population the sample represents does not equal 8. This is a **nondirectional alternative hypothesis**, and it is evaluated with a **two-tailed test**. In order to be supported, the absolute value of z must be equal to or greater than the tabled critical two-tailed z value at the prespecified level of significance. Thus, either a significant positive z value or a significant negative z value will provide support for this alternative hypothesis.)

or

$$H_1: \mu > 8$$

(The mean of the population the sample represents is greater than 8. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. It will only be supported if the sign of z is positive, and the absolute value of z is equal to or greater than the tabled critical one-tailed z value at the prespecified level of significance.)

or

$$H_1: \mu < 8$$

(The mean of the population the sample represents is less than 8. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. It will only be supported if the sign of z is negative, and the absolute value of z is equal to or greater than the tabled critical one-tailed z value at the prespecified level of significance.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis is rejected.

IV. Test Computations

Assume that the following values represent the scores of the sample of $n = 30$ subjects who take the test of visual-motor coordination in Example 1.1: 9, 10, 6, 4, 8, 11, 10, 5, 5, 6, 13, 12, 4, 4, 3, 9, 12, 5, 6, 6, 8, 9, 8, 5, 7, 9, 10, 9, 5, 4.

Since X_i can be employed to represent the score of the i^{th} subject, by adding all thirty scores we obtain: $\sum X_i = \sum X = 222$.

Equation 1.1 is used to compute the mean of the sample.

$$\bar{X} = \frac{\sum X}{n} \quad \text{(Equation 1.1)}$$

Employing Equation 1.1, we confirm that the mean of the sample is $\bar{X} = 7.4$, the value stated in Example 1.1.

$$\bar{X} = \frac{222}{30} = 7.4$$

Before the test statistic can be computed, it is necessary to compute a value that is referred to as the **standard error of the population mean**. This value, which is represented by the notation $\sigma_{\bar{X}}$, is computed with Equation 1.2. A full explanation of what $\sigma_{\bar{X}}$ represents can be found in Section VII.

$$\sigma_{\bar{X}} = \frac{\sigma}{\sqrt{n}} \quad \text{(Equation 1.2)}$$

Substituting the values $\sigma = 2$ and $n = 30$ in Equation 1.2, the value of $\sigma_{\bar{X}} = .36$ is computed.

$$\sigma_{\bar{X}} = \frac{2}{\sqrt{30}} = .36$$

It should be noted that $\sigma_{\bar{X}}$ can never be a negative value. If a negative value is obtained for $\sigma_{\bar{X}}$, it indicates a computational error has been made.

Equation 1.3 is employed to compute the value of z , which is the test statistic for the **single-sample z test**. Note that in Equation 1.3, the value that represents μ is the value $\mu = 8$ which is stated in the null hypothesis.

$$z = \frac{\bar{X} - \mu}{\sigma_{\bar{X}}} \quad \text{(Equation 1.3)}$$

Employing Equation 1.3, the value $z = -1.67$ is computed for Example 1.1.

$$z = \frac{7.4 - 8}{.36} = -1.67$$

Note that Equation 1.3 will always yield a positive z value when the sample mean is greater than the hypothesized value of μ . The value of z will always be negative when the sample mean is less than the hypothesized value of μ . When the sample mean is equal to the hypothesized value of μ , z will equal zero.

V. Interpretation of the Test Results

The obtained value $z = -1.67$ is evaluated with **Table A1 (Table of the Normal Distribution)** in the **Appendix**. **Table 1.1** summarizes the tabled critical two-tailed and one-tailed .05 and .01 z values listed in **Table A1**.

Table 1.1 Tabled Critical Two-Tailed and One-Tailed .05 and .01 z Values

	$z_{.05}$	$z_{.01}$
Two-tailed values	1.96	2.58
One-tailed values	1.65	2.33

The following guidelines are employed in evaluating the null hypothesis for the **single-sample z test**.

a) If the alternative hypothesis employed is nondirectional, the null hypothesis can be rejected if the obtained absolute value of z is equal to or greater than the tabled critical two-tailed value at the prespecified level of significance.

b) If the alternative hypothesis employed is directional and predicts a population mean larger than the value stated in the null hypothesis, the null hypothesis can be rejected if the sign of z is positive, and the value of z is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

c) If the alternative hypothesis employed is directional and predicts a population mean smaller than the value stated in the null hypothesis, the null hypothesis can be rejected if the sign of z is negative, and the absolute value of z is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

Employing the above guidelines, we can only reject the null hypothesis if the directional

alternative hypothesis $H_1: \mu < 8$ is employed, and the null hypothesis can only be rejected at the .05 level. This is the case, since the obtained value of z is a negative number, and the absolute value of z is greater than the tabled critical one-tailed .05 value $z_{.05} = 1.65$.¹ The alternative hypothesis $H_1: \mu < 8$ is not supported at the .01 level, since the absolute value $z = 1.67$ is not greater than the tabled critical one-tailed .01 value $z_{.01} = 2.33$.

The nondirectional alternative hypothesis $H_1: \mu \neq 8$ is not supported, since the obtained absolute value $z = 1.67$ is less than the tabled critical two-tailed .05 value $z_{.05} = 1.96$.

The directional alternative hypothesis $H_1: \mu > 8$ is not supported, since the obtained value $z = -1.67$ is a negative number. In order for the alternative hypothesis $H_1: \mu > 8$ to be supported, the computed value of z must be a positive number (as well as the fact that it must be equal to or greater than the tabled critical one-tailed value at the prespecified level of significance).

A summary of the analysis of Example 1.1 with the **single-sample z test** follows: With respect to the test of visual-motor coordination, we can conclude that the sample of 30 subjects comes from a population with a mean value other than 8 only if we employ the directional alternative hypothesis $H_1: \mu < 8$, and prespecify as our level of significance $\alpha = .05$. This result can be summarized as follows: $z = -1.67$, $p < .05$.

A more in-depth discussion of the interpretation of the z value computed with the **single-sample z test** is contained in Section VII.

VI. Additional Analytical Procedures for the Single-Sample z Test and/or Related Tests

Procedures are available for computing **power** and **confidence intervals** for the **single-sample z test**. These computations are discussed in Section VI of the **single-sample t test** (which employs the same protocol for such computations as does the **single-sample z test**).

VII. Additional Discussion of the Single-Sample z Test

1. The interpretation of a negative z value The actual range of scores on the abscissa (i.e., the X -axis) of the standard normal distribution is $-\infty \leq z \leq +\infty$. The guidelines outlined in Section V for interpreting negative z values are intended to provide the reader with the simplest and least confusing protocol for interpreting such values. In terms of the actual distribution of z values, it should be noted that although the tabled critical z values listed in [Table 1.1](#) are positive numbers, they are also applicable to interpreting negative z values. Since the critical values recorded in [Table 1.1](#) represent absolute values, the corresponding negative z values are listed in [Table 1.2](#).

Table 1.2 Tabled Critical Two-Tailed and One-Tailed .05 and .01 Negative z Values

	$z_{.05}$	$z_{.01}$
Two-tailed values	-1.96	-2.58
One-tailed values	-1.65	-2.33

Within the framework of the values noted in [Table 1.2](#), if one employs the directional (one-tailed) alternative hypothesis $H_1: \mu < 8$, in order to reject the null hypothesis, the obtained value of z must be a negative number that is **equal to or less than the prespecified tabled critical value**. Thus, to be significant at the .05 level, the obtained z value would have to be equal to or less than $z = -1.65$. The reader should take note of the fact that any negative number which has

an absolute value greater than 1.65 is less than -1.65 . In the same respect, in order for the alternative hypothesis $H_1: \mu < 8$ to be supported at the .01 level, the obtained z value would have to be equal to or less than $z = -2.33$, since any negative number which has an absolute value greater than 2.33 is less than -2.33 . The important thing for the reader to understand is that when one is dealing with a negative number, the larger the absolute value of the negative number, the lower the value of that number.

2. The standard error of the population mean and graphical representation of the results of the single-sample z test The intent of this section is to provide further clarification of what the z value computed with the **single-sample z test** represents. In order to do this, it is necessary to understand what is represented by the **standard error of the population mean** ($\sigma_{\bar{X}}$), which is the denominator of Equation 1.3. The standard error of the population mean represents a standard deviation of a **sampling distribution of means**. Although such a sampling distribution is theoretical and is based on an infinite number of samples, it is possible to construct an empirical sampling distribution that is based on a smaller number of sample means. In order to construct such a sampling distribution of means, a random sample consisting of n subjects is drawn from a population of N subjects. Upon doing this, the mean of the sample of n subjects is computed. Once again, employing the whole population of N subjects, a second random sample consisting of n subjects is selected, and the mean of that sample is computed. This process is repeated over and over again. At whatever point one decides to terminate the process, a large number of sample means will have been computed, each of which is based on a sample size of n subjects. The frequency distribution of these sample means (which will be distributed normally) is known as a sampling distribution of means. The mean of a sampling distribution (represented by the notation $\mu_{\bar{X}}$) that is based on an infinite number of sample means will be the same value as the population mean (μ). As the number of sample means used to construct a sampling distribution increases, the greater the likelihood that the computed value of the mean of the sampling distribution equals the value of μ . The standard deviation of a sampling distribution (i.e., the standard deviation of all of the sample means), is the **standard error of the population mean** ($\sigma_{\bar{X}}$), which in many sources is referred to as the **standard error of the mean**.²

The z value computed with Equation 1.3 represents the number of standard deviation units (based on the value of $\sigma_{\bar{X}}$) that the sample mean deviates from the hypothesized population mean. Thus in Example 1.1, the value $\sigma_{\bar{X}} = .36$ represents the standard deviation of a sampling distribution of means in which in each sample $n = 30$. The obtained value $z = -1.67$ indicates that $\bar{X} = 7.4$ (the sample mean) is 1.67 sampling distribution standard deviation units below the hypothesized population mean $\mu = 8$ (which as noted earlier has the same value as $\mu_{\bar{X}}$). The difference is statistically significant, since a sample mean of 7.4 obtained with 30 subjects is a relatively unlikely occurrence in a sampling distribution that has a mean of 8 and a standard deviation of .36. If we make the assumption that the distribution of means in the sampling distribution is normal, use of the **single-sample z test** will lead to the conclusion that if, in fact, the true value of the population mean is 8, the likelihood of obtaining a sample mean equal to or less than 7.4 is less than .05 (to be exact, it equals .0475).

Figure 1.1 provides a visual description of the sampling distribution of means for Example 1.1. In Figure 1.1, the numbers 6.92, 7.28, ..., 9.08 along the abscissa identify the values a sample mean will assume if it is 1, 2, and 3 standard deviation (sd) units below and above the mean of the sampling distribution. Since the value of one standard deviation unit for the sampling distribution under discussion is equal to $\sigma_{\bar{X}} = .36$, the value 8.36, which is one standard deviation unit above the mean of the distribution, is obtained simply by adding the value $\sigma_{\bar{X}} = .36$ to $\mu_{\bar{X}} = 8$. The value 8.72, which is two standard deviations above the mean, is obtained by adding two times the value of $\sigma_{\bar{X}}$ to $\mu_{\bar{X}} = 8$, and so on.

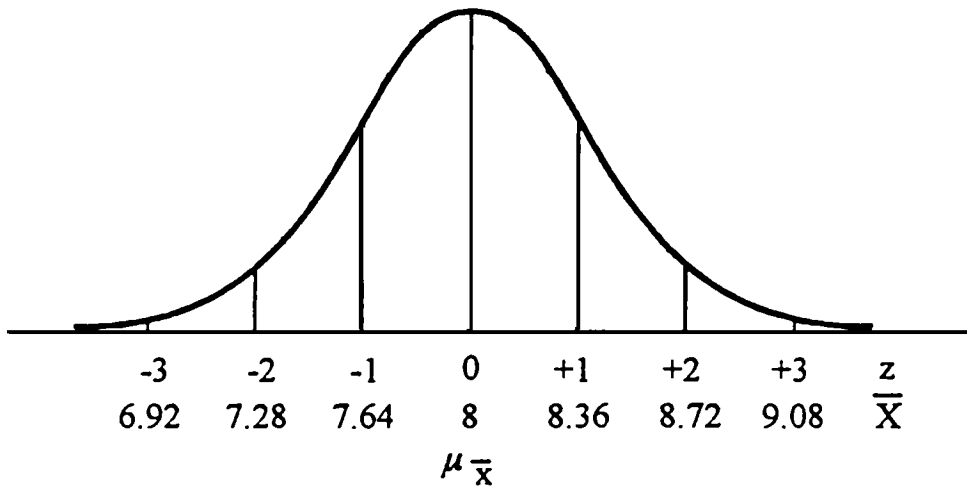


Figure 1.1 Sampling Distribution for Example 1.1

Since almost 100% of the cases in a normal distribution fall within three standard deviation units above or below the mean,³ if a researcher has a sample of 30 subjects that is derived from a population in which $\mu = 8$ and $\sigma = 2$, he can be almost 100% sure that the mean of the sample will fall between the values 6.92 and 9.08 (which are the values that correspond to the -3 sd and $+3$ sd points in Figure 1.1). A mean value outside of this range is highly unlikely to occur and, if a more extreme mean value does occur, it is reasonable to conclude that the sample is derived from a population which had a mean value other than 8.

Earlier in the discussion of a sampling distribution it was noted that it is assumed that the sample means are normally distributed. The basis for this statement is a general principle in mathematics known as the **central limit theorem**. The central limit theorem states that in a population with a mean value of μ and a standard deviation of σ , the following will be true with respect to the sampling distribution of means: a) The sampling distribution will have a mean value equal to μ and a standard deviation equal to $\sigma_{\bar{X}} = \sigma/\sqrt{n}$; and b) The sampling distribution approaches being normal as the size (n) of each of the samples employed in generating the sampling distribution increases, and as the total number of means used to generate the sampling distribution increases. Although the underlying population each of the samples is derived from does not, in itself, have to be normal, the more it approximates normality the lower the value of n required for the sampling distribution to be normal. In addition, the more the underlying population each of the samples is derived from approaches normality, the fewer sample means will be required before the sampling distribution becomes normal.

Based on what has been said with respect to the standard error of the population mean, one can determine the value that a sample mean will have to be equal to or more extreme than in order to reject a null hypothesis at a prespecified level of significance. Figure 1.2 depicts these values for Example 1.1 in reference to the tabled critical one- and two-tailed .05 and .01 z values. Note that in each of the graphs, the value that is written directly below the tabled critical z value for the relevant level of significance is the value the sample mean will have to be equal to or more extreme than in order to reject the null hypothesis $H_0: \mu = 8$.

The values that the sample mean must be equal to or more extreme than in Figure 1.2 are computed with Equation 1.4, which is the result of algebraically transposing the terms in Equation 1.3 in order to solve for the value of \bar{X} .

$$\bar{X} = \mu + z \sigma_{\bar{X}} \quad (\text{Equation 1.4})$$

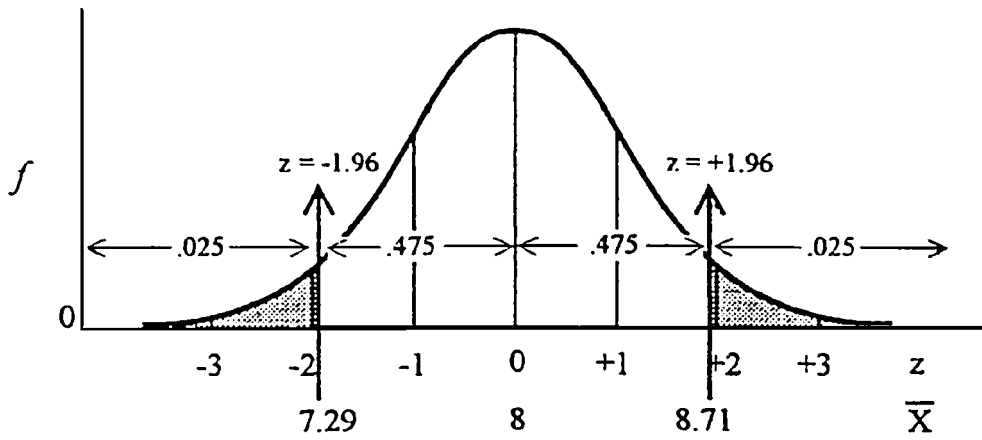


Figure 1.2a Distribution of Critical Two-Tailed .05 z Value for $H_1: \mu \neq 8$

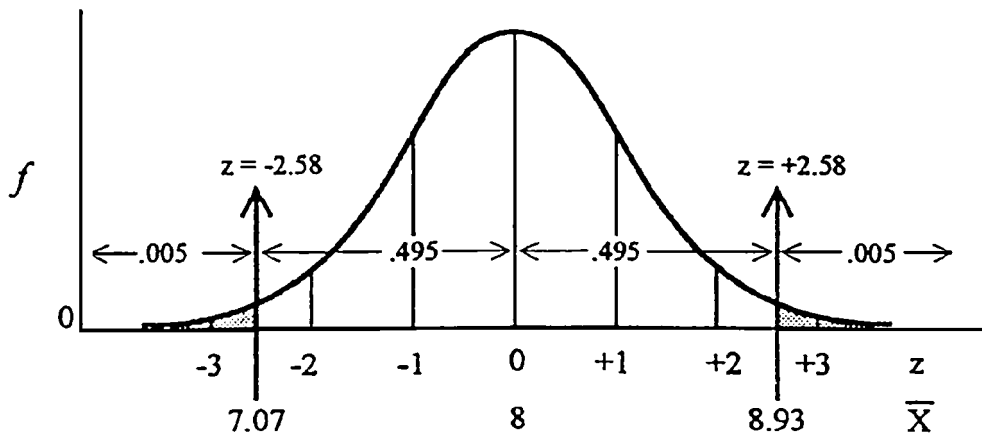


Figure 1.2b Distribution of Critical Two-Tailed .01 z Value for $H_1: \mu \neq 8$

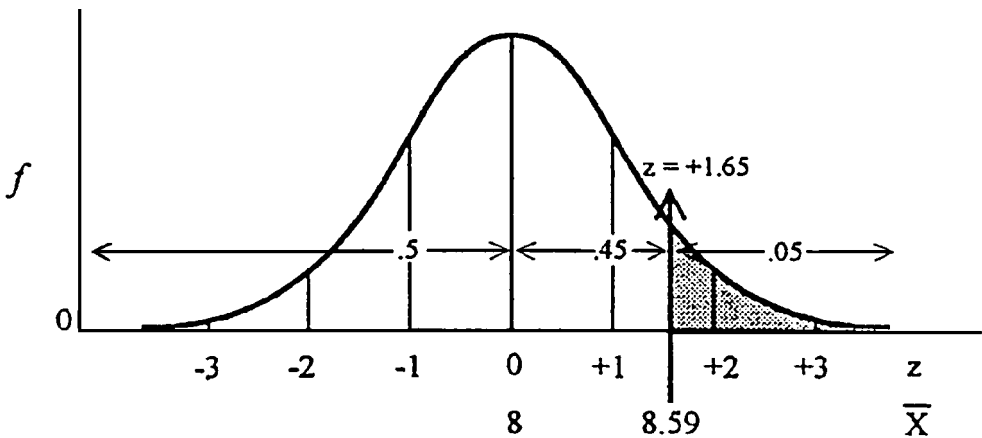


Figure 1.2c Distribution of Critical One-Tailed .05 z Value for $H_1: \mu > 8$

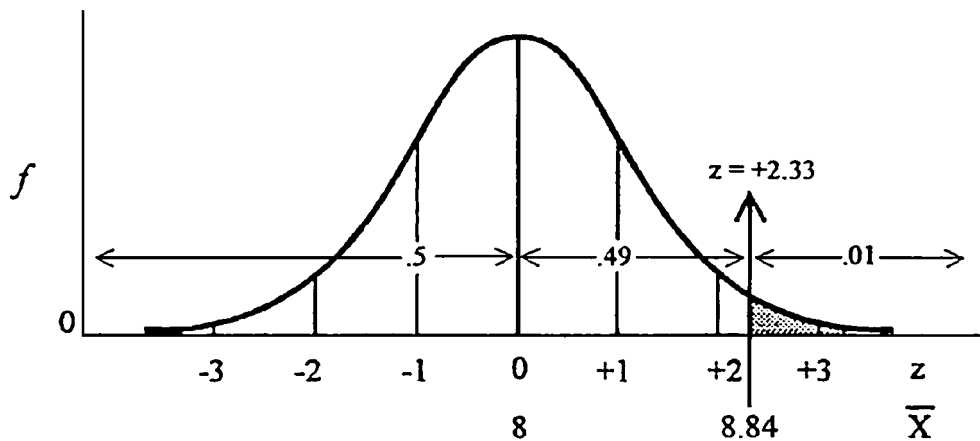


Figure 1.2d Distribution of Critical One-Tailed .01 z Value for $H_1: \mu > 8$

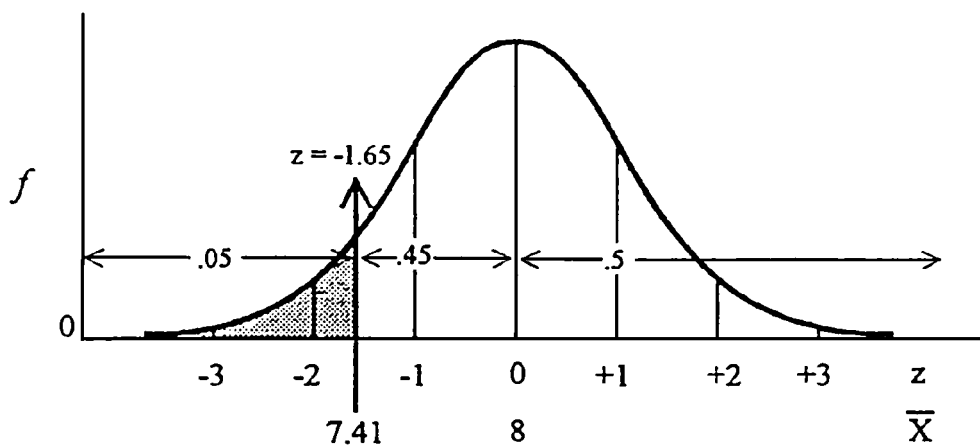


Figure 1.2e Distribution of Critical One-Tailed .05 z Value for $H_1: \mu < 8$

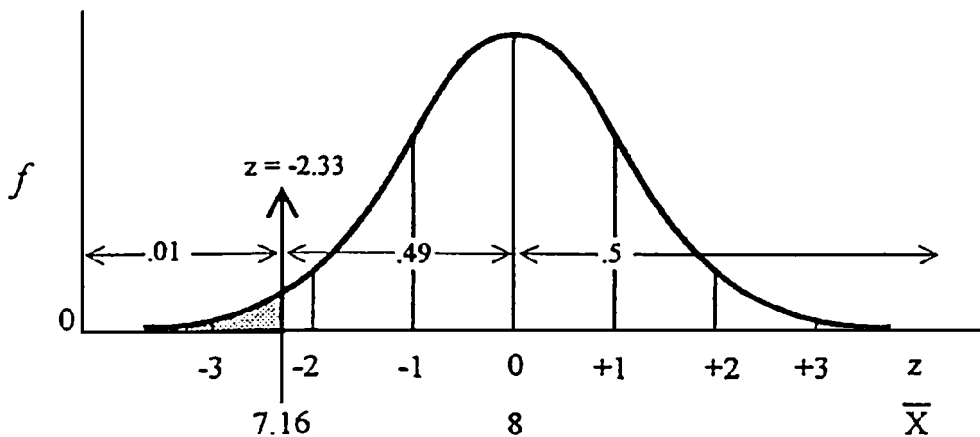


Figure 1.2f Distribution of Critical One-Tailed .01 z Value for $H_1: \mu < 8$

The value employed to represent z in Equation 1.4 is the relevant tabled critical z value at the prespecified level of significance. By multiplying the latter value by $\sigma_{\bar{X}}$ and adding and subtracting the product from the value of the population mean, one is able to compute the upper limit that the sample mean must be equal to or greater than and the lower limit that the sample mean must be equal to or less than in order for a result to be significant. This is illustrated below for the case depicted in Figure 1.2a, which describes the upper and lower limits for the sample mean when the nondirectional alternative hypothesis $H_1: \mu \neq 8$ is employed, with $\alpha = .05$.

$$\bar{X} = 8 \pm (1.96)(.36) = 8 \pm .71$$

Since $8 + .71 = 8.71$ and $8 - .71 = 7.29$, in order to be significant at the .05 level, a sample mean will have to be equal to or greater than 8.71, or equal to or less than 7.29. This result can be summarized as follows: $7.29 \geq \bar{X} \geq 8.71$.

A summary of the results depicted in Figure 1.2 follows:

Figure 1.2a: If the nondirectional alternative hypothesis $H_1: \mu \neq 8$ is employed, with $\alpha = .05$, in order to reject the null hypothesis, the obtained value of the sample mean will have to be equal to or greater than 8.71 or be equal to or less than 7.29.

Figure 1.2b: If the nondirectional alternative hypothesis $H_1: \mu \neq 8$ is employed, with $\alpha = .01$, in order to reject the null hypothesis, the obtained value of the sample mean will have to be equal to or greater than 8.93 or be equal to or less than 7.07.

Figure 1.2c: If the directional alternative hypothesis $H_1: \mu > 8$ is employed, with $\alpha = .05$, in order to reject the null hypothesis, the obtained value of the sample mean will have to be equal to or greater than 8.59.

Figure 1.2d: If the directional alternative hypothesis $H_1: \mu > 8$ is employed, with $\alpha = .01$, in order to reject the null hypothesis, the obtained value of the sample mean will have to be equal to or greater than 8.84.

Figure 1.2e: If the directional alternative hypothesis $H_1: \mu < 8$ is employed, with $\alpha = .05$, in order to reject the null hypothesis, the obtained value of the sample mean will have to be equal to or less than 7.41.

Figure 1.2f: If the directional alternative hypothesis $H_1: \mu < 8$ is employed, with $\alpha = .01$, in order to reject the null hypothesis, the obtained value of the sample mean will have to be equal to or less than 7.16.

Note that with respect to a specific alternative hypothesis in the above examples, the lower the value of alpha, the larger the value computed for an upper limit and the lower the value computed for a lower limit. Additionally, if the value of alpha is fixed, the computed value for an upper limit will be higher and the computed value for a lower limit will be lower when a nondirectional alternative hypothesis is employed, as opposed to when a directional alternative hypothesis is used.

3. Additional examples illustrating the interpretation of a computed z value To further clarify the interpretation of z values, Table 1.3 lists three additional z values that could have been obtained for Example 1.1 if a different set of data had been employed. Table 1.3 notes the decisions that would be made with reference to the three possible alternative hypotheses a researcher could employ on the basis of each of these z values. The table assumes that $H_0: \mu = 8$.

4. The z test for a population proportion Another test that employs the normal distribution in order to analyze data derived from a single sample is the **z test for a population proportion (Test 9a)**. Equation 9.6, the equation for computing the test statistic for the **z test for a population proportion**, is a special case of Equation 1.3. The use of Equation 9.6 is reserved for

evaluating a set of scores for a binomially distributed variable (for which the values of μ and σ can be determined). The **z test for a population proportion** is discussed after a full discussion of the binomial distribution (which can be found under the **binomial sign test for a single sample (Test 9)**).

Table 1.3 Decision Table for z Values

Obtained z value	Alternative hypothesis	Decision
1.75	$H_1: \mu \neq 8$	The null hypothesis cannot be rejected, since the obtained value $z = 1.75$ is less than the tabled critical two-tailed .05 and .01 values $z_{.05} = 1.96$ and $z_{.01} = 2.58$.
	$H_1: \mu > 8$	The null hypothesis can be rejected at the .05 level of significance, since the obtained value $z = 1.75$ is a positive number which is greater than the tabled critical one-tailed .05 value $z_{.05} = 1.65$. The null hypothesis cannot be rejected at the .01 level, since it is less than the tabled critical one-tailed .01 value $z_{.01} = 2.33$.
	$H_1: \mu < 8$	The null hypothesis cannot be rejected, since the obtained value $z = 1.75$ is a positive number.
-2.75	$H_1: \mu \neq 8$	The null hypothesis can be rejected at both the .05 and .01 levels of significance, since the obtained absolute value $z = 2.75$ is greater than the tabled critical two-tailed .05 and .01 values $z_{.05} = 1.96$ and $z_{.01} = 2.58$.
	$H_1: \mu > 8$	The null hypothesis cannot be rejected, since the obtained value $z = -2.75$ is a negative number.
	$H_1: \mu < 8$	The null hypothesis can be rejected at both the .05 and .01 levels of significance, since the obtained value $z = -2.75$ is a negative number and the absolute value $z = 2.75$ is greater than the tabled critical one-tailed .05 and .01 values $z_{.05} = 1.65$ and $z_{.01} = 2.33$.
.75	$H_1: \mu \neq 8$	The null hypothesis cannot be rejected, since the obtained value $z = .75$ is less than the tabled critical two-tailed .05 and .01 values $z_{.05} = 1.96$ and $z_{.01} = 2.58$.
	$H_1: \mu > 8$	The null hypothesis cannot be rejected, since the obtained value $z = .75$ is less than the tabled critical one-tailed .05 and .01 values $z_{.05} = 1.65$ and $z_{.01} = 2.33$.
	$H_1: \mu < 8$	The null hypothesis cannot be rejected, since the obtained value $z = .75$ is a positive number.

VIII. Additional Examples Illustrating the Use of the Single-Sample z Test

Five additional examples that can be evaluated with the **single-sample z test** are presented in this section. Since Examples 1.2–1.4 employ the same population parameters and data set used in Example 1.1, they yield the identical result. Note that Examples 1.2 and 1.3 employ objects in lieu of subjects. Examples 1.5 and 1.6 illustrate the application of the **single-sample z test** when the size of the sample is $n = 1$.

Example 1.2. *The Brite battery company manufactures batteries which are programmed by a computer to have an average life span of 8 months and a standard deviation of 2 months. If the average life of a random sample of 30 Brite batteries purchased from 30 different stores is 7.4 months, are the data consistent with the mean value parameter programmed into the computer?*

Example 1.3. *The Smooth Road cement company stores large quantities of its cement in 30 storage tanks. A state law says that the machine which fills the tanks must be calibrated so as not to deviate substantially from a mean load of 8 tons. It is known that the standard deviation of the loads delivered by the machine is 2 tons. An inspector visits the storage facility and determines that the mean number of tons in the 30 storage tanks is 7.4 tons. Does this conform to the requirements of the state law?*

Example 1.4. *A study involving 30 subjects is conducted in order to determine the subjects' ability to accurately judge weight. In the study subjects are required (by adding or subtracting sand) to adjust the weight of a cylinder, referred to as the variable stimulus, until it is judged equal in weight to a standard comparison cylinder whose weight is fixed. The weight of the standard comparison stimulus is 8 ounces. Prior research has indicated that the standard deviation of the subjects' judgements in such a task is 2 ounces. Prior to testing the subjects, the experimenter decides she will conclude that a kinesthetic illusion occurs if the mean of the subjects' judgements differs significantly from the value of the standard stimulus. If the average weight assigned by the 30 subjects to the variable stimulus is 7.4 ounces, can the experimenter conclude that a kinesthetic illusion has occurred?*

Example 1.5. *A meteorologist determines that during the current year there were 80 major storms recorded in the Western Hemisphere. He claims that 80 storms represent a significantly greater number than the annual average. Based on data that have been accumulated over the past 100 years, it is known that on the average there have been 70 major storms in the Western Hemisphere, and the standard deviation is 2. (We will assume the distribution for the number of storms per year is normal.) Do 80 storms represent a significant deviation from the mean value of 70?*

Example 1.5 illustrates a problem that would be evaluated with the **single-sample z test** in which the value of n is equal to one. In the example, the sample size of one represents the single year during which there were 80 storms. When the value of $n = 1$, Equation 1.3 becomes Equation 1.5 (which is the same as Equation I.27 in the **Introduction**).

$$z = \frac{X - \mu}{\sigma} \quad \text{(Equation 1.5)}$$

Equation 1.5, the equation for converting a raw score into a standard deviation (z) score, allows one to determine the likelihood of a specific score occurring within a normally distributed population. Thus, within the context of Example 1.5, Equation 1.5 will allow the meteorologist to determine the likelihood that a score of 80 will occur in a normally distributed population in which $\mu = 70$ and $\sigma = 2$. The analysis assumes that within the total population there are $N = 100$ scores (where each score represents the number of storms in a given year during the 100-year period). Since the frequency of storms during one year is being compared to the population mean, the value of $n = 1$. Note that when $n = 1$, the value of the sample mean (\bar{X}) in Equation 1.3 reduces to the value X in Equation 1.5. Additionally, since $n = 1$, the value of $\sigma_{\bar{X}}$ in Equation 1.3 becomes σ in Equation 1.5, since $\sigma_{\bar{X}} = \sigma/\sqrt{n} = \sigma/\sqrt{1} = \sigma$.

Employing Equations 1.3/1.5 with the data for Example 1.5, the value $z = 5$ is computed.

$$z = \frac{80 - 70}{2} = 5$$

The null hypothesis employed for the above analysis is $H_0: \mu = 70$. Example 1.5 implies that either the directional alternative hypothesis $H_1: \mu > 70$ or the nondirectional alternative

hypothesis $H_1: \mu \neq 70$ can be employed. Regardless of which of these alternative hypotheses is employed, since the computed value $z = 5$ is greater than all of the tabled critical values in [Table 1.1](#), the null hypothesis can be rejected at both the .05 and .01 levels. Thus, the meteorologist can conclude that a significantly greater number of storms were recorded during the current year than the mean value recorded for the past 100 years. The directional alternative hypothesis $H_1: \mu < 70$ is not supported, since, in order to support the latter alternative hypothesis, the computed value of z must be a negative number (which will only be the case if the number of storms observed during the year is less than the population mean of $\mu = 70$).

Example 1.6. *A physician assesses the level of a specific chemical in a 40-year-old male patient's blood. Assume that the average level of the chemical in adult males is 70 milligrams (per 100 milliliters), with a standard deviation of 2 milligrams (per 100 milliliters). If the patient has a blood reading of 80, will the patient be viewed as abnormal?*

As is the case in Example 1.5, Example 1.6 also employs a sample size of $n = 1$. Since this example uses the same data as Example 1.5, the computed value $z = 5$ is obtained, thus allowing the physician to reject the null hypothesis. The value $z = 5$ indicates that the patient has a blood reading that is five standard deviation units above the population mean. The proportion of cases in the normal distribution associated with a z score of 5 or greater is so small that there is no tabled value listed for $z = 5$ in [Table A1](#).

Reference

Freund, J. E. (1984). **Modern elementary statistics** (6th ed.). Englewood Cliffs, NJ: Prentice–Hall, Inc.

Endnotes

1. The exact probability value recorded for $z = 1.67$ in Column 3 of [Table A1](#) is .0475 (which is equivalent to 4.75%). This indicates that the proportion of cases that falls above the value $z = 1.67$ is .0475, and the proportion of cases that falls below the value $z = -1.67$ is .0475. Since this indicates that in the left tail of the distribution there is less than a 5% chance of obtaining a z value equal to or less than $z = -1.67$, we can reject the null hypothesis at the .05 level if we employ the nondirectional alternative hypothesis $H_1: \mu < 8$, with $\alpha = .05$.
2. Equation 1.2 is employed to compute the standard error of the population mean when the size of the underlying population is infinite. In practice, it is employed when the size of the underlying population is large and the size of the sample is believed to constitute less than 5% of the population. However, among others, Freund (1984) notes that in a finite population, if the size of a sample constitutes more than 5% of the population, a correction factor is introduced into Equation 1.2. The computation of the standard error of the mean with the **finite population correction factor** is noted below:

$$\sigma_{\bar{X}} = \frac{\sigma}{\sqrt{n}} \sqrt{\frac{N - n}{N - 1}}$$

Where: N represents the total number of subjects/objects that comprise the population.

The finite population corrected equation will result in a smaller value for $\sigma_{\bar{X}}$. This is the

case, since as the proportion of a population represented by a sample increases, the less variability there will be among the means that comprise the sampling distribution, and thus the smaller the expected difference between the sample mean obtained for a set of data and the value of the population mean. Thus when $n = N$, employing the finite corrected equation, the value of $\sigma_{\bar{x}}$ will always equal zero. This is the case since when $n = N$, the sample mean and population mean will always be the same value, and thus no error is involved in estimating the value of $\mu_{\bar{x}}$. Since it is usually assumed that the size of a sample is less than 5% of the population it represents, Equation 1.2 is the only equation listed in most sources for computing the value of $\sigma_{\bar{x}}$.

3. Inspection of **Table A1** reveals that the exact percentage of cases in a normal distribution that falls within three standard deviations above or below the mean is 99.74%.

Test 2

The Single-Sample t Test (Parametric Test Employed with Interval/Ratio Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test Does a sample of n subjects (or objects) come from a population in which the mean (μ) equals a specified value?

Relevant background information on test The **single-sample t test** is one of a number of inferential statistical tests that are based on the t distribution. Like the normal distribution, the t distribution is a bell-shaped, continuous, symmetrical distribution, which to the statistically unsophisticated eye is almost indistinguishable from the normal distribution. t , which is the computed test statistic for the **single-sample t test**, represents a standard deviation score, and is interpreted in the same manner as the z value computed for the **single-sample z test**. The only difference between a z value and a t value is that for a given standard deviation score, the proportion of cases that falls between the mean and the standard deviation score will be a function of which of the two distributions one employs. Except when $n = \infty$, for a given standard deviation score, a larger proportion of cases falls between the mean of the normal distribution and the standard deviation score than the proportion of cases that falls between the mean and that same standard deviation score in the t distribution. In point of fact, there are actually an infinite number of t distributions — each distribution being based on the number of subjects/objects in the sample. As the size of the sample increases, the proportions (and consequently the critical values) in the t distribution approach the proportions (and critical values) in the normal distribution, and, in fact, when $n = \infty$, the normal and t distributions are identical. A more detailed discussion (as well as visual illustrations) of the t distribution can be found in Section VII.

The **single-sample t test** is employed in a hypothesis testing situation involving a single sample in order to determine whether or not a sample with a mean of \bar{X} is derived from a population with a mean of μ . If the result of the **single-sample t test** yields a significant difference, the researcher can conclude there is a high likelihood the sample is derived from a population with a mean value other than μ .

The **single-sample t test** is used with interval/ratio data. The test is employed when a researcher does not know the value of the population standard deviation (σ), and therefore must estimate it by computing the sample standard deviation (\bar{s}). As is noted in the discussion of the **single-sample z test (Test 1)**, some sources argue that even if one knows the value of σ , when the sample size is very small (generally less than 25), the **single sample t test** provides a more accurate estimate of the underlying sampling distribution for the data.

The following two assumptions which are noted for the **single-sample z test**, also apply to the **single-sample t test**: a) The sample has been randomly selected from the population it represents; and b) The distribution of data in the underlying population the sample represents is normal. If either of the aforementioned assumptions is saliently violated, the reliability of the t test statistic may be compromised.

II. Example

Example 2.1 *A physician states that the average number of times he sees each of his patients during the year is five. In order to evaluate the validity of this statement, he randomly selects ten of his patients and determines the number of office visits each of them made during the past year. He obtains the following values for the ten patients in his sample: 9, 10, 8, 4, 8, 3, 0, 10, 15, 9. Do the data support his contention that the average number of times he sees a patient is five?*

III. Null versus Alternative Hypotheses

Null hypothesis $H_0: \mu = 5$

(The mean of the population the sample represents equals 5.)

Alternative hypothesis $H_1: \mu \neq 5$

(The mean of the population the sample represents does not equal 5. This is a **nondirectional alternative hypothesis**, and it is evaluated with a **two-tailed test**. In order to be supported, the absolute value of t must be equal to or greater than the tabled critical two-tailed t value at the prespecified level of significance. Thus, either a significant positive t value or a significant negative t value will provide support for this alternative hypothesis.)

or

$H_1: \mu > 5$

(The mean of the population the sample represents is greater than 5. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. It will only be supported if the sign of t is positive, and the absolute value of t is equal to or greater than the tabled critical one-tailed t value at the prespecified level of significance.)

or

$H_1: \mu < 5$

(The mean of the population the sample represents is less than 5. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. It will only be supported if the sign of t is negative, and the absolute value of t is equal to or greater than the tabled critical one-tailed t value at the prespecified level of significance.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis is rejected.

IV. Test Computations

Table 2.1 summarizes the number of visits recorded for the $n = 10$ subjects in Example 2.1. In order to compute the test statistic for the **single-sample t test**, it is necessary to determine the mean of the sample and to obtain an unbiased estimate of the population standard deviation.

Employing Equation 1.1 (which is the same as Equation I.1 in the **Introduction**) the mean of the sample is computed to be $\bar{X} = 7.6$.

$$\bar{X} = \frac{\sum X}{n} = \frac{76}{10} = 7.6$$

Table 2.1 Summary of Data for Example 2.1

Battery	X	X^2
1	9	81
2	10	100
3	8	64
4	4	16
5	8	64
6	3	9
7	0	0
8	10	100
9	15	225
10	9	81
$\Sigma X = 76$		$\Sigma X^2 = 740$

Equation 2.1 (which is the same as Equation I.8 in the **Introduction**) is employed to compute \tilde{s} , which represents an unbiased estimate of the value of the population standard deviation.

$$\tilde{s} = \sqrt{\frac{\Sigma X^2 - \frac{(\Sigma X)^2}{n}}{n - 1}} \quad (\text{Equation 2.1})$$

Using Equation 2.1, the value $\tilde{s} = 4.25$ is computed.

$$\tilde{s} = \sqrt{\frac{740 - \frac{(76)^2}{10}}{9 - 1}} = 4.25$$

As is the case with the **single-sample z test**, computation of the test statistic for the **single-sample t test** requires that the value of the **standard error of the population mean** be computed. $s_{\bar{X}}$, which represents an estimate of $\sigma_{\bar{X}}$, is computed with Equation 2.2. Note that $s_{\bar{X}}$, which is referred to as the **estimated standard error of the population mean**, is based on the value of \tilde{s} computed with Equation 2.1. A discussion of the theoretical meaning of the standard error of the population mean can be found in Section VII of the **single-sample z test**. Further discussion of $s_{\bar{X}}$ (which represents a standard deviation of a sampling distribution of means and is interpreted in the same manner as $\sigma_{\bar{X}}$) can be found in Section V.

$$s_{\bar{X}} = \frac{\tilde{s}}{\sqrt{n}} \quad (\text{Equation 2.2})$$

Employing Equation 2.2, the value $s_{\bar{X}} = 1.34$ is computed.

$$s_{\bar{X}} = \frac{4.25}{\sqrt{10}} = 1.34$$

It should be noted that neither \tilde{s} or $s_{\bar{X}}$ can ever be a negative value. If a negative value is obtained for either \tilde{s} or $s_{\bar{X}}$, it indicates a computational error has been made.

Equation 2.3 is the test statistic for the **single-sample t test**.¹

$$t = \frac{\bar{X} - \mu}{s_{\bar{X}}} \quad (\text{Equation 2.3})$$

Inspection of Equation 2.3 reveals that it is similar in structure to Equation 1.3, the equation for the **single-sample z test**. The only differences between the two equations are that: a) Equation 2.3 employs the t distribution as opposed to the z distribution; and b) The value of the standard error of the population mean is estimated in Equation 2.3 from the value of \tilde{s} .²

Employing Equation 2.3, the value $t = 1.94$ is computed. Note that in Equation 2.3, the value that represents μ is the value $\mu = 5$ which is stated in the null hypothesis.

$$t = \frac{7.6 - 5}{1.34} = 1.94$$

V. Interpretation of the Test Results

Since, like a z value, a t value represents a standard deviation score, except for the fact that a different distribution is employed, it is interpreted in the same manner. The obtained value $t = 1.94$ is evaluated with **Table A2 (Table of Student's t Distribution)** in the **Appendix**.³ In **Table A2** the critical t values are listed in relation to the proportion of cases (which are recorded at the top of each column) that falls below a specified t score in the t distribution, and the number of **degrees of freedom** for the sampling distribution that is being evaluated (which are recorded in the left hand column of each row). Equation 2.4 is employed to compute the degrees of freedom for the **single-sample t test**. A full explanation of the meaning of the degrees of freedom can be found in Section VII.

$$df = n - 1 \quad \text{(Equation 2.4)}$$

Employing Equation 2.4, we compute that $df = 10 - 1 = 9$. Thus, the tabled critical t values that are employed in evaluating the results of Example 2.1 are the values recorded in the cells of **Table A2** that fall in the row for $df = 9$ and the columns with probabilities/proportions that correspond to the one- and two-tailed .05 and .01 values. These critical t values are summarized in **Table 2.1**.

Table 2.1 Tabled Critical Two-Tailed and One-Tailed .05 and .01 t Values

	$t_{.05}$	$t_{.01}$
Two-tailed values	2.26	3.25
One-tailed values	1.83	2.82

Note that the tabled critical two-tailed value $t_{.05} = 2.26$ is the value in the row $df = 9$ and the column $p = .975$, since $t_{.05} = 2.26$ is the standard deviation score above which (as well as below which in the case of $t = -2.26$) a proportion equivalent to .025 of the cases in the distribution falls. The tabled critical two-tailed value $t_{.01} = 3.25$ is the value in the row $df = 9$ and the column $p = .995$, since $t_{.01} = 3.25$ is the standard deviation score above which (as well as below which in the case of $t = -3.25$) a proportion equivalent to .005 of the cases in the distribution falls. The tabled critical one-tailed value $t_{.05} = 1.83$ is the value in the row $df = 9$ and the column $p = .95$, since $t_{.05} = 1.83$ is the standard deviation score above which (as well as below which in the case of $t = -1.83$) a proportion equivalent to .05 of the cases in the distribution falls. The tabled critical one-tailed value $t_{.01} = 2.82$ is the value in the row $df = 9$ and the column $p = .99$, since $t_{.01} = 2.82$ is the standard deviation score above which (as well as below which in the case of $t = -2.82$) a proportion equivalent to .01 of the cases in the distribution falls.

The following guidelines are employed in evaluating the null hypothesis for the **single-sample t test**.

a) If the alternative hypothesis employed is nondirectional, the null hypothesis can be rejected if the obtained absolute value of t is equal to or greater than the tabled critical two-tailed value at the prespecified level of significance.

b) If the alternative hypothesis employed is directional and predicts a population mean larger than the value stated in the null hypothesis, the null hypothesis can be rejected if the sign of t is positive and the value of t is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

c) If the alternative hypothesis employed is directional and predicts a population mean smaller than the value stated in the null hypothesis, the null hypothesis can be rejected if the sign of t is negative and the absolute value of t is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

Employing the above guidelines, we can only reject the null hypothesis if the directional alternative hypothesis $H_1: \mu > 5$ is employed, and the null hypothesis can only be rejected at the .05 level. This is the case since the obtained value of t is a positive number which is greater than the tabled critical one-tailed .05 value $t_{.05} = 1.83$. Note that the alternative hypothesis $H_1: \mu > 5$ is not supported at the .01 level, since the obtained value $t = 1.94$ is less than the tabled critical one-tailed .01 value $t_{.01} = 2.82$.

The nondirectional alternative hypothesis $H_1: \mu \neq 5$ is not supported since the obtained value $t = 1.94$ is less than the tabled critical two-tailed .05 value $t_{.05} = 2.26$.

The directional alternative hypothesis $H_1: \mu < 5$ is not supported since the obtained value $t = 1.94$ is a positive number. In order for the alternative hypothesis $H_1: \mu < 5$ to be supported, the computed value of t must be a negative number (as well as the fact that the absolute value of t must be equal to or greater than the tabled critical one-tailed value at the prespecified level of significance).

In Section IV it is noted that the **estimated standard error of the population mean** ($s_{\bar{x}}$) computed for the **single-sample t test** represents a standard deviation of a sampling distribution of means. The use of the t distribution for Example 2.1 is based on the fact that when the population standard deviation is unknown, the latter distribution provides a better approximation of the underlying sampling distribution than does the normal distribution. [Figure 2.1](#) depicts the sampling distribution employed for Example 2.1. This sampling distribution is interpreted in the same manner as the sampling distribution for the **single-sample z test** which is depicted in [Figure 1.1](#).

Inspection of the sampling distribution depicted in [Figure 2.1](#) reveals that the obtained value $t = 1.94$ falls to the right of the tabled critical one-tailed value $t_{.05} = 1.83$. At this point it should be noted that $t_{.05} = 1.83$ is greater than $z_{.05} = 1.65$, the tabled critical one-tailed .05 value employed with the normal distribution. Both of these values demarcate the upper 5% of their respective distributions. If one elects to employ the **single-sample z test**, as opposed to the **single-sample t test**, for an analysis in which the value of σ is unknown, it will inflate the likelihood of committing a Type I error. This is the case since, except when the sample size is very large (in which case the corresponding values of t and z are identical), a tabled critical z value at a prespecified level of significance will always be smaller than the corresponding tabled critical t value at that same level of significance. Thus, in the case of Example 2.1, if we employ the tabled critical one-tailed value $z_{.05} = 1.65$, the likelihood of committing a Type I error will be greater than .05. This can be confirmed by inspection of [Table A2](#) which indicates that for $df = 9$, the proportion of cases in the t distribution that falls at or above the value of $t = 1.65$ is greater than .05 (i.e., a t score of 1.65 falls below the 95th percentile of the distribution).⁴

A summary of the analysis of Example 2.1 with the **single-sample t test** follows: With respect to the average number of times the doctor sees a patient, we can conclude that the sample

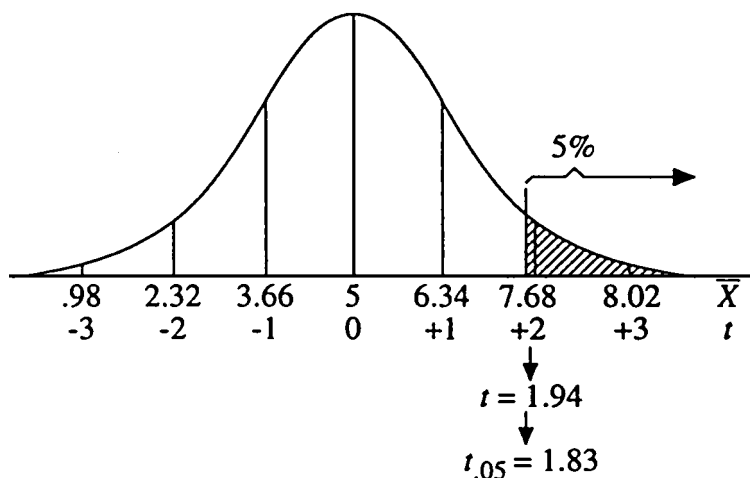


Figure 2.1 Sampling Distribution for Example 2.1

of 10 subjects comes from a population with a mean value other than 5 only if we employ the directional alternative hypothesis $H_1: \mu > 5$, and prespecify as our level of significance $\alpha = .05$. This result can be summarized as follows: $t(9) = 1.94, p < .05$. (The degrees of freedom employed in the analysis are noted in parentheses after the t .)

VI. Additional Analytical Procedures for the Single-Sample t Test and/or Related Tests

1. Determination of the power of the single-sample t test and the single-sample z test, and the application of Test 2a: Cohen's d index The power of either the **single-sample z test** or the **single-sample t test** will represent the probability of the test identifying a difference between the value for the population mean stipulated in the null hypothesis and a specific value that represents the true value of the mean of the population represented by the experimental sample. In order to compute the power of a test, it is necessary for the researcher to stipulate the latter value which will be identified with the notation μ_1 . In practice, a researcher can compute the power of a test for any value of μ_1 .

The power of the test will be a function of the difference between the value of μ stated in the null hypothesis and the value of μ_1 . The test's power will increase as the absolute value of the difference between the values μ and μ_1 increases. This is the case, since if the sample is derived from a population with a mean value that is substantially above or below the value of μ stated in the null hypothesis, it is likely that this would be reflected in the value of the sample mean (\bar{X}). Obviously, the more the value of \bar{X} deviates from the hypothesized value of μ , the greater the absolute value of the numerators (i.e., $\bar{X} - \mu$) in Equations 1.3 and 2.3 (which are, respectively, the equations for the **single-sample z test** and the **single-sample t test**). Assuming that the value of the denominator is held constant, the larger the value of the numerator, the larger the absolute value of the computed test statistic (i.e., z or t). The larger the latter value the more likely it is that the researcher will be able to reject the null hypothesis (assuming the obtained difference is in the direction predicted in the alternative hypothesis), and consequently the more powerful the test.

Since the obtained value of the test statistic is also a function of the denominator of Equations 1.3 and 2.3 (i.e., the actual or estimated standard error of the population mean), the latter value also influences the power of the test. Specifically, as the value of the denominator decreases, the computed absolute value of the test statistic increases. It happens to be the case that

the value of the standard error of the mean is a function of the population standard deviation (which is estimated in the case of the t test) and the sample size. Inspection of Equations 1.3 and 2.3 reveals that the standard error of the mean will decrease if the value of the standard deviation is decreased and the sample size is increased. Thus, by employing an accurate estimate of the population standard deviation (more specifically, in the case of the t test, one that is not spuriously inflated due to sampling error) and a large sample size, one can minimize the value of the denominator in Equations 1.3 and 2.3, and consequently maximize the absolute value of the test statistic. As a result, one can increase the likelihood that the null hypothesis will be rejected, which increases the power of the test.

The power of a statistical test can be represented both mathematically and graphically. Figures 2.2 and 2.3 illustrate the concept of power and its relationship to the Type I and Type II error rates. Both figures contain two distributions which represent the sampling distributions of means for two populations.⁵ In each figure, the sampling distribution on the left represents a population with the mean μ (i.e., the value stated in the null hypothesis). The sampling distribution on the right represents a population with the mean μ_1 , which we will assume is the true value of the mean of the population from which the experimental sample is derived. Figures 2.2 and 2.3 both assume a fixed value for the sample size upon which the sampling distributions are based, and that each of the underlying populations represented by the sampling distributions has the same standard deviation. Figure 2.2 represents a case in which there is a large difference between the values of μ_1 and μ , whereas Figure 2.3 represents a case in which there is a small difference between the two values. When expressed in standard deviation units, the magnitude of the absolute value of the difference between μ_1 and μ is referred to as the **effect size**. Thus, in Figure 2.2 a **large effect size** is present, whereas Figure 2.3 depicts a **small effect size**.

The reader should note the following with respect to Figures 2.2 and 2.3.

a) The closer the values μ and μ_1 are to one another, the more the sampling distributions of the two populations overlap.

b) In the case of a one-tailed analysis, the value of alpha (α) is represented by area (///) in the distribution on the left. Recollect that α represents the likelihood of committing a Type I error (i.e., rejecting a true null hypothesis). Numerically, α represents the proportion of the left distribution that comprises area (///). In the case of a two-tailed analysis, the proportion of the left distribution represented by area (///) will be equal to $\alpha/2$.

c) The value of beta (β) is represented by area (≡) in the distribution on the right. β represents the likelihood of committing a Type II error (i.e., retaining a false null hypothesis). Numerically, β represents the proportion of the right distribution that comprises area (≡).

d) The power of the test is represented by area (\\) in the right distribution. Note that this is the area in the right distribution that falls to the right of the area delineating β . Numerically, the power of the test represents the proportion of the right distribution that comprises area (\\). The power of the test can also be represented by subtracting the value of β from 1 (i.e., Power = $1 - \beta$). Note that the area in the left distribution that represents α overlaps the area in the right distribution representing the power of the test.

e) In order to increase the value of α , one must move the boundary in the left distribution that delineates α to the left. By doing the latter, one will decrease the value of β , since the area in the right distribution that corresponds to β will decrease. By increasing the value of α , one also increases the area in the right distribution which represents the power of the test. This illustrates the fact that if one increases the likelihood of committing a Type I error (α), one decreases the likelihood of committing a Type II error (β), and at the same time increases the power of the test ($1 - \beta$). In the same respect, to decrease the value of α one must move the boundary in the left distribution that delineates alpha to the right. By doing the latter, one will increase the value of β , since the area in the right distribution that corresponds to β will increase. By decreasing the

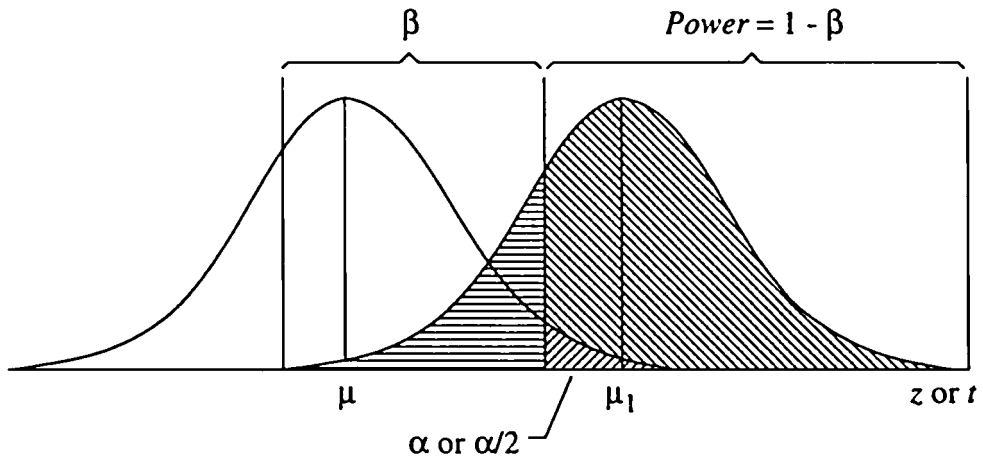


Figure 2.2 Sampling Distributions Employed in Determining the Power of a Test Involving a Large Effect Size

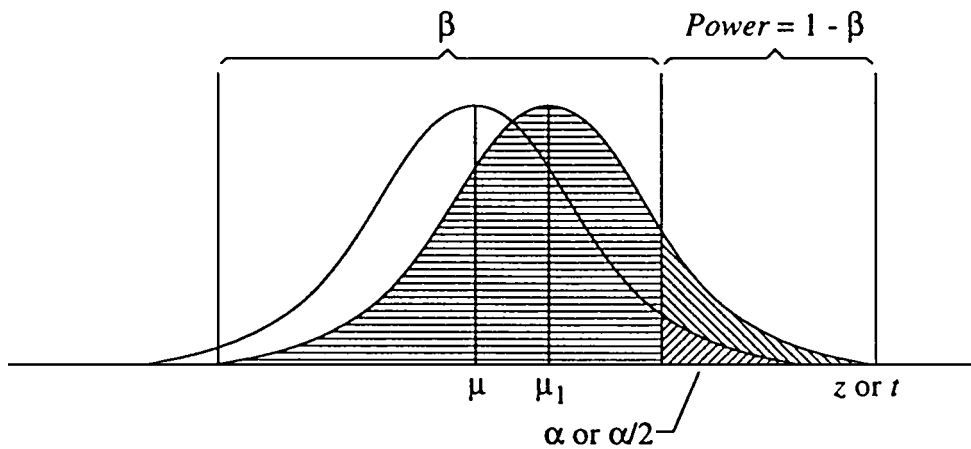


Figure 2.3 Sampling Distributions Employed in Determining the Power of a Test Involving a Small Effect Size

value of α , one also decreases the area in the right distribution which represents the power of the test. This illustrates the fact that if one decreases the likelihood of committing a Type I error, the likelihood of committing a Type II error increases, and at the same time the power of the test decreases.

f) It should also be noted that at a given level of significance, a one-tailed test will be more powerful than a two-tailed test. This is the case since with a one-tailed test the point that delineates α will be farther to the left in the left distribution than will be the case with a two-tailed test. As an example, when $\alpha = .05$, the tabled critical one-tailed value for z is $z_{.05} = 1.65$, whereas the tabled critical two-tailed value is $z_{.05} = 1.96$. Since both of these critical values are in the left distribution, the former value will be farther to the left, thus expanding the area in the right distribution which represents the power of the test.

Two methods will now be demonstrated which can be used to determine the power of either the **single-sample t test** or the **single-sample z test**. The first method (which is more time consuming) reveals all of the logical operations involved in computing the power of a test. The

second method, which employs **Table A3 (Power Curves for Student's t Distribution)** in the **Appendix**, requires fewer computations. It should be emphasized that whenever possible, a power analysis should be conducted prior to the data collection phase of a study. By computing power beforehand, one is able to design a study with a sample size that is large enough to detect the specific effect size predicted by the researcher.

Method 1 for computing the power of the single-sample t test and the single sample z test

The first method will initially be demonstrated with reference to the **single-sample z test**. The reason for employing the latter test is that it will allow us to use **Table A1 (Table of the Normal Distribution)** in the **Appendix**, which lists probabilities for all z values between 0 and 4. Detailed tables of the t distribution that list probabilities for all t values within this range are generally not available.

Let us assume that in our example we are employing the same null hypothesis that is employed in Example 2.1 (i.e., $H_0: \mu = 5$). It will be assumed that the researcher wishes to evaluate the power of the **single-sample z test** in reference to the alternative hypothesis $H_1: \mu_1 = 6$. Note that in conducting a power analysis, the alternative hypothesis states that the population mean is a specific value that is different from the value stated in H_0 . In conducting the power analysis, it will be assumed that the null hypothesis will be evaluated with a two-tailed test, with $\alpha = .05$. For purposes of illustration, it will also be assumed that the researcher evaluates the null hypothesis employing a sample size of $n = 121$. In addition, we will assume that the value of the population standard deviation is known to be $\sigma = 4.25$.

Employing Equation 1.2, the value of the standard error of the population mean is computed. Thus: $\sigma_{\bar{X}} = 4.25/\sqrt{121} = .39$.

Figure 2.4, which depicts the analysis graphically, is comprised of two overlapping normal distributions. Each distribution is a sampling distribution of population means. The distribution on the left, which is the sampling distribution of means of a population with a mean of 5, will be referred to as Distribution A. The distribution on the right, which is the sampling distribution of means of a population with a mean of 6, will be referred to as Distribution B. We have already determined above that $\sigma_{\bar{X}} = .39$, and we will assume that this value represents the standard deviation of each of the sampling distributions. The area (///) delineates the proportion of Distribution A that corresponds to the value $\alpha/2$, which equals .025. This is the case, since $\alpha = .05$ and a two-tailed test is being used. In such an instance, the proportion of the curve comprising the critical area in each of the tails of Distribution A will be $.05/2 = .025$. Area (=) delineates the proportion of Distribution B that corresponds to the probability of committing a Type II error (β). Area (\\) delineates the proportion of Distribution B that represents the power of the test.

The procedure for computing the proportions in **Figure 2.4** will now be described. The first step in computing the power of the test requires one to determine how far above the value $\mu = 5$ the sample mean will have to be in order to reject the null hypothesis. Equation 1.3 is employed to determine this minimum required difference. By algebraically transposing the terms in Equation 1.3 we can determine that $\bar{X} - \mu = (z_{.05})(\sigma_{\bar{X}})$. Thus, by substituting the values $z_{.05} = 1.96$ (which is the tabled critical two-tailed .05 z value) and $\sigma_{\bar{X}} = .39$ in the latter equation we can compute that the minimum required difference is $\bar{X} - \mu = (1.96)(.39) = .76$.

Thus, any sample mean .76 units above or below the value $\mu = 5$ will allow the researcher to reject the null hypothesis at the .05 level (if a two-tailed analysis is employed). With respect to evaluating the power of the test in reference to the alternative hypothesis $H_1: \mu_1 = 6$, the researcher is only concerned with a mean value above 5 (which will fall in the right tail of Distribution A).⁶ Thus, a mean value of $\bar{X} = 5.76$ or greater will allow the researcher to reject the null hypothesis (since $\mu + (z_{.05})(\sigma_{\bar{X}}) = 5 + .76 = 5.76$).

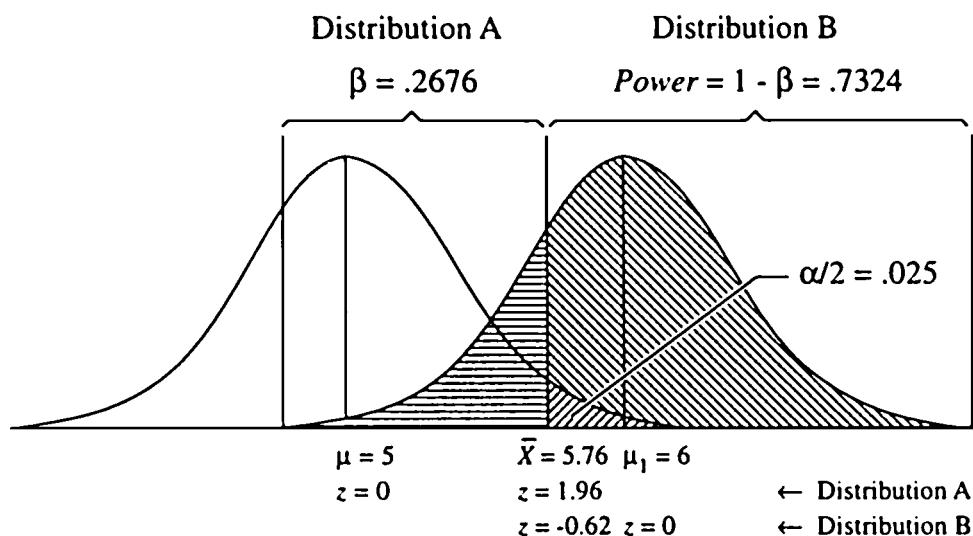


Figure 2.4 Visual Representation of Power when $H_0: \mu = 5$ and $H_1: \mu = 6$ for $n = 121$

The next step in the analysis requires that the area in Distribution B that falls between the mean $\mu_1 = 6$ and the value 5.76 be computed. This is accomplished by employing Equation 1.3 and substituting 5.76 to represent the value of \bar{X} and $\mu_1 = 6$ to represent the value of μ .

$$z = \frac{\bar{X} - \mu}{\sigma_{\bar{X}}} = \frac{5.76 - 6}{.39} = -.62$$

Utilizing [Table A1](#), we determine that the proportion of Distribution B that lies between $\mu_1 = 6$ and 5.76 (i.e., between the mean and a z score of $-.62$ or $+.62$) is .2324. Since the value 5.76 is below the mean of Distribution B, if .5 (which is the proportion of Distribution B that falls above the mean $\mu_1 = 6$) is added to .2324, the resulting value of .7324 will represent the power of the test. This latter value is represented by area (///) in [Figure 2.4](#). The likelihood of committing a Type II error (i.e., β) is represented by area (=). The proportion of Distribution B that constitutes this latter area is determined by subtracting the value .7324 from 1. Thus: $\beta = 1 - .7324 = .2676$. Based on the results of the power analysis we can state that if the alternative hypothesis $H_1: \mu_1 = 6$ is true, the likelihood that the null hypothesis will be rejected is .7324, and, at the same time, there is a .2676 likelihood that it will be retained. If the researcher considered the computed value for the power too low (which we are assuming is determined prior to implementing the study), she can increase the power of the test by employing a larger sample size.

If the value of σ is not known and has to be estimated from the sample data, the power analysis will be based on the t distribution instead of the normal distribution. In such a case the identical protocol described above for computing power is employed, except for the fact that a tabled critical t value is used in place of the tabled critical z value. Unless the sample size is extremely large, the tabled critical t value will be larger than the tabled critical z value used for the same data. As a result of this, the power of the test computed for the t distribution will be lower than the value computed for the normal distribution.

In the case of the example under discussion, if the t distribution is employed one would use the tabled critical two-tailed .05 t value for $df = n - 1 = 121 - 1 = 120$. From [Table A2](#) it can be determined that this value is $t_{.05} = 1.98$. Using the latter value and the value $s_{\bar{X}} = .39$, it can

be determined that .77 is the minimum required difference in order to achieve significance. When .77 is added to the value $\mu = 5$, it indicates that a sample mean of 5.77 or greater (as well as 4.23 or lower) will allow the researcher to reject the null hypothesis. The t value required to complete the power calculations is determined by utilizing Equation 2.3 and substituting 5.77 to represent the value of \bar{X} and $\mu_1 = 6$ to represent the value of μ . The calculations are noted below.

$$(t_{.05})(s_{\bar{X}}) = \bar{X} - \mu$$

$$(1.98)(.39) = .77$$

$$t = \frac{5.77 - 6}{.39} = -.59$$

Detailed tables of the t distribution indicate that for $df = 120$ the proportion of cases between the mean and a t score of $-.59$ or $+.59$ is approximately .22.⁷ The power of the test is derived by adding .5 to the latter value. Thus, Power = .22 + .5 = .72, which is slightly lower than the value .7324 obtained for the normal distribution.

It was previously noted that the size of the sample employed in a study is directly related to the power of a statistical test. Thus, in the example under discussion, if instead of using a sample size of $n = 121$, we employ a sample size of $n = 10$, the power of both the **single-sample z test** and the **single-sample t test** will be considerably less than the computed values .7324 and .72. In point of fact, when $n = 10$ the power of the **single-sample z test** equals .1122. The dramatic decrease in power for the small sample size can be understood by determining the minimum amount by which \bar{X} and μ must differ from one another in order to reject the null hypothesis. Since we are still employing the normal distribution, when $n = 10$ the same tabled critical two-tailed value $z_{.05} = 1.96$ is used. However, the value of $\sigma_{\bar{X}}$ is increased substantially, since $\sigma_{\bar{X}} = 4.25/\sqrt{10} = 1.34$. Employing the values $z_{.05} = 1.96$ and $\sigma_{\bar{X}} = 1.34$, we can compute that the minimum required difference in order to reject H_0 when $n = 10$ is 2.63. Specifically: $\bar{X} - \mu = (1.96)(1.34) = 2.63$.

A sample mean that is 2.63 units above $\mu = 5$ is equal to 7.63. The latter value will fall farther to the right in the right tail of Distribution B than the value 5.76 which is computed when $n = 121$. Substituting the values $\bar{X} = 7.63$ and $\mu = 6$ in Equation 1.3, we determine that $\bar{X} = 7.63$ is 1.22 standard deviation units above the mean of Distribution B.

$$z = \frac{7.63 - 6}{1.34} = 1.22$$

If one examines Figure 2.5, which depicts the analysis graphically, it can be seen that in Distribution B the value $z = 1.22$ lies to the right of the mean of the distribution. Thus, when $n = 10$ the power of the **single-sample z test** will be represented by the proportion of Distribution B that comprises area (\\). Employing the table for the normal distribution, it can be determined that the proportion of the curve to the right of $z = 1.22$ is .1122, which represents the power of the test. On the basis of this, we can determine that the likelihood of committing a Type II error (represented by area (=)) will be $\beta = 1 - .1122 = .8878$, which is substantially greater than the value .2676 obtained when $n = 121$. Note that area (\\) in Distribution B is much smaller than the corresponding area depicted in Figure 2.4 (when $n = 121$). By virtue of area (\\) being smaller, the proportion of Distribution B in Figure 2.5 representing area (=) is substantially larger than the corresponding proportion/area in Figure 2.4.

The t distribution will now be applied to the above problem. Let us assume that $n = 10$ and the value of σ is unknown. The latter value, however, is estimated from the sample data to be

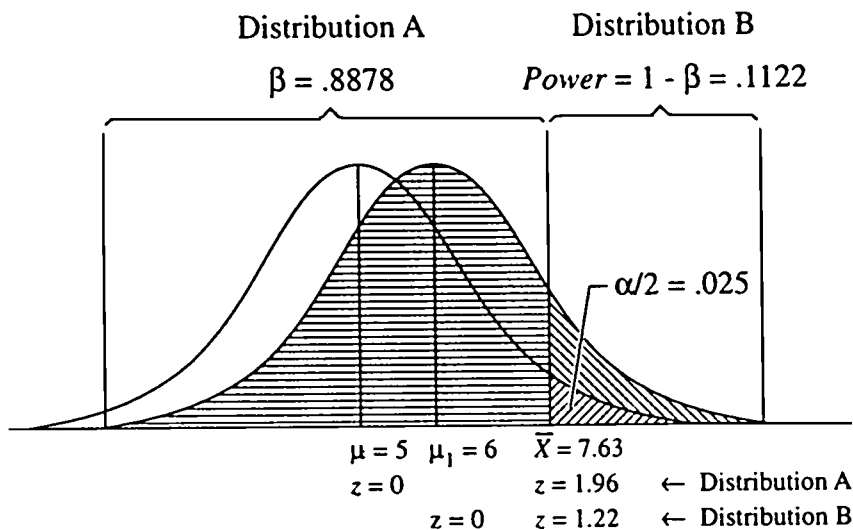


Figure 2.5 Visual Representation of Power when $H_0: \mu = 5$ and $H_1: \mu = 6$ for $n = 10$

$\bar{s} = 4.25$. The aforementioned values $n = 10$ and $\bar{s} = 4.25$ correspond to those employed in Example 2.1. If one wants to compute the power of the **single-sample t test** for Example 2.1 with reference to the alternative hypothesis $H_1: \mu_1 = 6$, the same protocol as described above for the normal distribution is employed, except for the fact that the value $t_{.05} = 2.26$ (which is the tabled critical two-tailed .05 t value for $df = 9$) is used in the analysis. Thus:

$$\begin{aligned}
 t_{.05} s_{\bar{X}} &= \bar{X} - \mu \\
 (2.26)(1.34) &= 3.03 \\
 t &= \frac{8.03 - 6}{1.34} = 1.51
 \end{aligned}$$

The use of the value $\bar{X} = 8.03$ in the t test equation above is predicated on the fact that a mean of 8.03 is 3.03 units above the value $\mu = 5$ stated in the null hypothesis. Detailed tables of the t distribution indicate that for $df = 9$, the proportion of cases that falls above a t score of 1.51 is approximately .085 (which corresponds to area (\\)) in Figure 2.5 if the latter represented the t distribution).⁸ The value .085 represents the power of the test. The likelihood of committing a Type II error (which corresponds to area (≡)) is $\beta = 1 - .085 = .915$.

A comparison of the values obtained for the power of the **single-sample z test** and the **single-sample t test** for the two sample sizes employed in the discussion of power (i.e., for $n = 121$ and $n = 10$), reveals that when the values of both n and the standard deviation are fixed, the **single-sample z test** provides a more powerful test of an alternative hypothesis than does the **single-sample t test** (keeping in mind, however, that the use of the **single-sample z test** is justified only if the value of σ is known).

Test 2a: Cohen's d index (Method 2 for computing the power of the single-sample t test and the single-sample z test) It was noted previously that when the magnitude of the absolute value of the difference between μ_1 and μ is expressed in standard deviation units, the resulting value is referred to as the **effect size**. The computation of effect size, represented by the notation d , can

be summarized by Equation 2.5. Throughout the book, the d statistic computed with the Equation 2.5 will be referred to as **Cohen's d index**, since it was first employed as a measure of effect size by Jacob Cohen (1977, 1988).

$$d = \frac{|\mu_1 - \mu|}{\sigma} \quad (\text{Equation 2.5})$$

In the above equation, in the case of the **single-sample z test** the value of σ will be known, whereas in the case of the **single-sample t test** the latter value will have to be estimated (either from the sample data or from prior research). Cohen (1977; 1988, pp. 24–27) has proposed the following (admittedly arbitrary) d values as criteria for identifying the magnitude of an effect size: a) A **small effect size** is one that is greater than .2 but not more than .5 standard deviation units; b) A **medium effect size** is one that is greater than .5 but not more than .8 standard deviation units; c) A **large effect size** is greater than .8 standard deviation units.

Note that in Equation 2.5 the effect size is based on population parameters and does not take into account the size of the sample. Since the power of a test is also a function of sample size, it is necessary to convert the value of d into a measure that takes into account both the population parameters and the sample size. This measure, represented by the notation δ (which is the lower case Greek letter **delta**), is referred to as the **noncentrality parameter**. The value of δ is computed with Equation 2.6.⁹

$$\delta = d\sqrt{n} \quad (\text{Equation 2.6})$$

If the value of δ is computed for a specific sample size, the power of both the **single-sample z test** and the **single-sample t test** can be determined by using **Table A3** in the **Appendix**, which consists of four sets of power curves in which the value of δ is plotted in reference to the power of a test. Each set of power curves is based on a different level of significance. Specifically: **Table A3-A** is employed for either a two-tailed analysis with $\alpha = .01$ or a one-tailed analysis with $\alpha = .005$. **Table A3-B** is employed for either a two-tailed analysis with $\alpha = .02$ or a one-tailed analysis with $\alpha = .01$. **Table A3-C** is employed for either a two-tailed analysis with $\alpha = .05$ or a one-tailed analysis with $\alpha = .025$. **Table A3-D** is employed for either a two-tailed analysis with $\alpha = .10$ or a one-tailed analysis with $\alpha = .05$. Note that each set of power curves is comprised of either eight or ten curves, each of which represents a different degrees of freedom value. When the degrees of freedom computed for an experiment do not equal one of the df values represented by the curves, the researcher must interpolate to approximate the power of the test. Regardless of the sample size, the curve for $df = \infty$ should always be used in determining the power of the **single-sample z test**. The latter curve is also used for the **single-sample t test** for large sample sizes.

The protocol for employing the curves in **Table A3** is as follows: a) Compute the value of δ ; b) Upon locating δ on the horizontal axis of the appropriate set of curves, draw a line that is perpendicular to the axis which intersects the curve that represents the appropriate df value; and c) At the point the line intersects the curve, drop a perpendicular to the vertical axis on which power values are noted. The point at which the latter line intersects the vertical axis will indicate the power of the test.

The noncentrality parameter will now be employed to compute the power of the **single-sample z test** and the **single-sample t test** using the same data employed to demonstrate Method 1. Thus, the power analysis will assume that the null hypothesis will be evaluated with a two-tailed test, with $\alpha = .05$. In addition:

$$H_0: \mu = 5 \quad H_1: \mu_1 = 6 \quad \sigma = \bar{s} = 4.25 \quad n = 121$$

Employing Equation 2.5, the value $d = .235$ is computed.

$$d = \frac{6 - 5}{4.25} = .235$$

Note that using Cohen's (1977, 1988) criteria for effect size, the value $d = .235$ indicates that we are attempting to detect a small effect size.

For $n = 121$, Equation 2.6 is employed to calculate the value $\delta = 2.59$.

$$\delta = (.235)\sqrt{121} = 2.59$$

Employing the power curve for $df = \infty$ in [Table A3-C](#), the power of the **single-sample z test** is determined to be approximately .73. Since there is no curve for $df = 120$, the power of the **single-sample t test** is based on a curve that falls between the $df = \infty$ and $df = 24$ power curves. Through interpolation, the power of the **single-sample t test** is determined to be approximately .72. Note that these are the same values that are computed with Method 1.

For the same example, with $n = 10$, $\delta = (.235)\sqrt{10} = .743$. Employing the power curve for $df = \infty$, the power of the **single-sample z test** is determined to be approximately .11. Since $df = 9$, using the $df = 6$ and $df = 12$ power curves as reference points, we determine that the power of the **single-sample t test** is approximately .085. These values are consistent with those computed with Method 1.

It should be emphasized again that, whenever possible, prior to the data collection phase of a study, a researcher should stipulate the minimum effect size that she is attempting to detect. The smaller the effect size, the larger the sample size that will be required in order to have a test of sufficient power that will allow one to reject a false null hypothesis. As long as a researcher knows or is able to estimate (from the sample data) the population standard deviation, by employing trial and error one can substitute various values of n in Equation 2.6 until the computed value of δ corresponds to the desired value for the power of the test. Power tables developed by Cohen (1977, 1988) are commonly employed within the framework of the present discussion as a quick means of determining the minimum sample size necessary to achieve a specific level of power in reference to a specific effect size.

In closing the discussion of power, it should be noted that if a researcher employs a large enough sample size, a significant difference can be obtained almost 100% of the time. Over the years various researchers have pointed out that the value of a sample mean is rarely if ever equal to the value of μ stated in the null hypothesis — in other words, that the null hypothesis is rarely if ever true. Obviously a researcher must discern whether or not a statistically significant difference that reflects a minimal effect size is of any practical or theoretical significance. In instances where it is not, for all practical purposes, if one rejects the null hypothesis under such circumstances, one is committing a Type I error. Criticisms that have been directed toward the conventional hypothesis testing model (i.e., the model that rejects the null hypothesis of zero difference when a result is statistically significant) are addressed in the discussion of **meta-analysis and related topics**, which can be found in Section IX (the **Addendum**) of the **Pearson product-moment correlation coefficient (Test 28)**.

2. Computation of a confidence interval for the mean of the population represented by a sample The hypothesis testing procedure described for the **single-sample t test** and the **single-sample z test** merely allows the researcher to determine whether or not it is reasonable to

conclude that the mean of a population is equal to a specific value. **Interval estimation**, another methodology used in inferential statistics (which is discussed briefly in the **Introduction**), allows a researcher to specify a range of values within which she can be confident the true value of a population parameter falls. One such interval which can be computed from sample data is referred to as a **confidence interval**.

In this section the procedure for computing a confidence interval for the mean of a population will be described. The confidence interval for the mean is a range of values within which a researcher can be confident to a specified degree that the true value of the population mean falls. When the value of the population standard deviation is unknown, computation of a confidence interval for a single sample involving interval/ratio data utilizes the t distribution. The following confidence intervals are most commonly computed: a) The 95% confidence interval stipulates the range of values within which one can be 95% confident the true population mean falls. Stated in probabilistic terms, there is a .95 probability/likelihood that the true value of the population mean falls within the range of values that define the 95% confidence interval; b) The 99% confidence interval stipulates the range of values within which one can be 99% confident the true population mean falls. Stated in probabilistic terms, there is a .99 probability/likelihood that the true value of the population mean falls within the range of values that define the 99% confidence interval.

Equation 2.7 is the general equation for computing a confidence interval for a population mean.

$$CI_{(1-\alpha)} = \bar{X} \pm (t_{\alpha/2})(s_{\bar{X}}) \quad \text{(Equation 2.7)}$$

Where: $t_{\alpha/2}$ represents the tabled critical two-tailed value in the t distribution, for $df = n - 1$, below which a proportion (percentage) equal to $[1 - (\alpha/2)]$ of the cases falls. If the proportion (percentage) of the distribution that falls within the confidence interval is subtracted from 1 (100%), it will equal the value of α .

Equation 2.8 is employed to compute the 95% confidence interval, which will be represented by the notation $CI_{.95}$ (since .95 is equivalent to 95%).

$$CI_{.95} = \bar{X} \pm (t_{.05})(s_{\bar{X}}) \quad \text{(Equation 2.8)}$$

In Equation 2.8, $t_{.05}$ represents the tabled critical two-tailed .05 t value for $df = n - 1$. By employing the latter critical t value, one will be able to identify the range of values within the sampling distribution that define the middle 95% of the distribution. Only 5% of the scores in the sampling distribution will fall outside that range. Specifically, 2.5% of the scores will fall above the upper limit of the range, and 2.5% of the scores will fall below the lower limit of the range.

Equation 2.9 is employed to compute the 99% confidence interval, which will be represented by the notation $CI_{.99}$ (since .99 is equivalent to 99%).

$$CI_{.99} = \bar{X} \pm (t_{.01})(s_{\bar{X}}) \quad \text{(Equation 2.9)}$$

Note that the only difference between Equation 2.9 and Equation 2.8 is that in Equation 2.9 the critical value $t_{.01}$ is employed. The latter value represents the tabled critical two-tailed .01 value for $df = n - 1$. By using the two-tailed $t_{.01}$ value, one will be able to identify the range of values within the sampling distribution that define the middle 99% of the distribution. Only 1% of the scores in the sampling distribution will fall outside that range. Specifically, .5% of the scores will fall above the upper limit of the range, and .5% of the scores will fall below the lower limit of the range.

The values $\bar{X} = 7.6$, $s_{\bar{X}} = 1.34$, and $t_{.05} = 2.26$ will now be substituted in Equation 2.8 to compute the 95% confidence interval for the mean of the population employed in Example 2.1.

$$CI_{.95} = 7.6 \pm (2.26)(1.34) = 7.6 \pm 3.03$$

The above result can be summarized as follows: $4.57 \leq \mu \leq 10.63$. The notation $4.57 \leq \mu \leq 10.63$ means that the value of μ is greater than or equal to 4.57 and less than or equal to 10.63. This result tells us that if a mean of $\bar{X} = 7.6$ is computed for a sample size of $n = 10$, we can be 95% confident (or the probability is .95) that the true value of the mean of the population the sample represents falls between the values 4.57 and 10.63. Thus, with respect to Example 2.1, the physician can be 95% confident that the average number of visits per patient is between 4.57 and 10.63.

Equation 2.9 will now be employed to compute the 99% confidence interval for the population mean in Example 2.1.

$$CI_{.99} = 7.6 \pm (3.25)(1.34) = 7.6 \pm 4.36$$

The above result can be summarized as follows: $3.24 \leq \mu \leq 11.96$. This result tells us that if a mean of $\bar{X} = 7.6$ is computed for a sample size of $n = 10$, we can be 99% confident (or the probability is .99) that the true value of the mean of the population the sample represents falls between the values 3.24 and 11.96. Thus, with respect to Example 2.1, the physician can be 99% confident that the average number of visits per patient is between 3.24 and 11.96.

Note that the range of values which defines the 99% confidence interval is larger than the range of values that defines the 95% confidence interval. This will always be the case, since it is only logical that by stipulating a larger range of values one will be able to have a higher degree of confidence that the true value of the population mean has been included within that range. It is also the case that the larger the sample size employed in computing a confidence interval, the smaller the range of values that will define the confidence interval. Figures 2.6 and 2.7 provide a graphical summary of the computation of the 95% and 99% confidence intervals.

Note that in Figure 2.6 the following is true: a) 47.5% of the scores in the sampling distribution fall between the sample mean $\bar{X} = 7.6$ and 4.57, the lower limit of $CI_{.95}$; and b) 47.5% of the scores in the sampling distribution fall between the sample mean $\bar{X} = 7.6$ and 10.63, the upper limit of $CI_{.95}$. Thus, the area of the curve between the scores 4.57 and 10.63 represents the middle 95% of the sampling distribution. Two and one-half percent of the scores in the distribution fall below 4.57 and 2.5% of the scores fall above 10.63. The scores which are below 4.57 or greater than 10.63 comprise the extreme 5% of the sampling distribution.

In Figure 2.7 the following is true: a) 49.5% of the scores in the sampling distribution fall between the sample mean $\bar{X} = 7.6$ and 3.24, the lower limit of $CI_{.99}$; and b) 49.5% of the scores in the sampling distribution fall between the sample mean $\bar{X} = 7.6$ and 11.96, the upper limit of $CI_{.99}$. Thus, the area of the curve between the scores 3.24 and 11.96 represents the middle 99% of the sampling distribution. One-half of one percent of the scores in the distribution fall below 3.24 and .5% of the scores fall above 11.96. The scores which are below 3.24 or greater than 11.96 comprise the extreme 1% of the sampling distribution.

The reader should take note of the fact that in Figures 2.6 and 2.7 the sample mean is employed to represent the mean of the sampling distribution. This is in contrast to the sampling distribution depicted in Figure 2.1, where the hypothesized value of the population mean is employed to represent the mean of the sampling distribution. The reason for using different means for the two sampling distributions is that the sampling distribution depicted in Figure 2.1 is used to determine the likelihood of a sample mean deviating from the hypothesized value of the

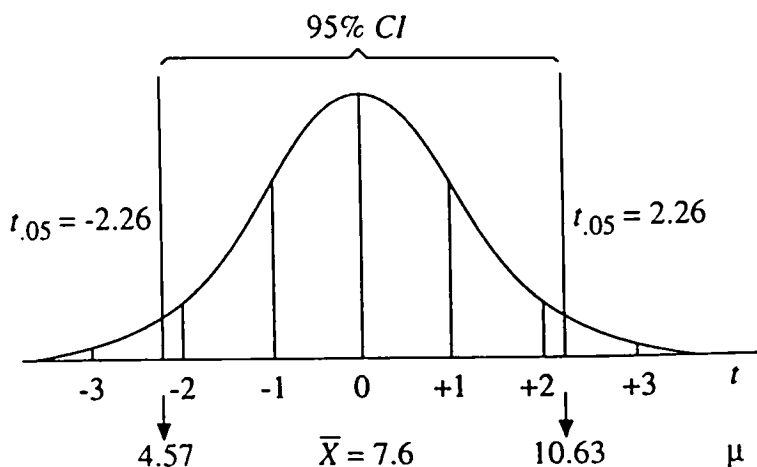


Figure 2.6 Graphical Representation of 95% Confidence Interval for Example 2.1

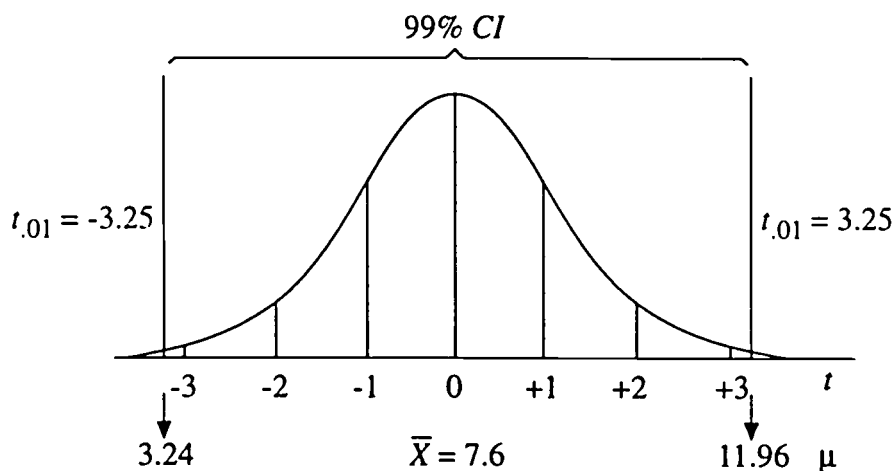


Figure 2.7 Graphical Representation of 99% Confidence Interval for Example 2.1

population mean, while the sampling distribution depicted in Figures 2.6 and 2.7 reflects the fact that one is engaged in interval estimation, and is thus employing the sample mean to predict the true value of the population mean.

Although, as noted previously, $CI_{.95}$ and $CI_{.99}$ are the most commonly computed confidence intervals, it is possible to calculate a confidence interval at any level of confidence. Thus, if one wanted to compute the 90% confidence interval, the equation $CI_{.90} = \bar{X} \pm (t_{.10})(s_{\bar{X}})$ is employed. In the latter equation $t_{.10}$ represents the tabled critical one-tailed .05 t value (which is also the tabled critical two-tailed .10 t value), since the latter values (which for $df = 9$ is $t = 1.83$) establishes the boundaries for the middle 90% of the sampling distribution. Only 10% of the scores in the sampling distribution will fall outside that range (5% of the scores will fall above the upper limit of the range, and 5% of the scores will fall below the lower limit of the range). Thus, for Example 2.1:

$$CI_{.90} = 7.6 \pm (1.83)(1.34) = 7.6 \pm 2.45 \quad \text{Thus: } 5.15 \leq \mu \leq 10.05$$

Employing the same logic, the 98% confidence interval can be computed by using the tabled critical one-tailed .01 value $t_{.01} = 2.82$ in the confidence interval equation. The latter t value is employed, since it establishes the boundaries for the middle 98% of the sampling distribution. Thus:

$$CI_{.98} = 7.6 \pm (2.82)(1.34) = 7.6 \pm 3.78 \quad \text{Thus: } 3.82 \leq \mu \leq 11.38$$

It should be noted that in order to accurately compute a confidence interval, one must have access to tables of the t distribution which provide the appropriate tabled value for the confidence interval in question. Since most published tables of the t distribution provide only the tabled critical one- and two-tailed .05 and .01 values, they only allow for accurate computation of the following confidence intervals: $CI_{.90}$, $CI_{.95}$, $CI_{.98}$, $CI_{.99}$. **Table A2** is more detailed than most tables of the t distribution, and thus it allows for accurate computation of a greater number of confidence intervals than those noted above. In instances where an exact t value is not tabled, interpolation can be used to estimate that value.

Although the computation of confidence intervals is not described in the discussion of the **single-sample z test**, when the value of the population standard deviation is known, the normal distribution (as opposed to the t distribution) is employed to compute a confidence interval. If a researcher knows the value of the population standard deviation, Equation 2.10 is the general equation for computing a confidence interval.

$$CI_{(1-\alpha)} = \bar{X} \pm (z_{\alpha/2})(\sigma_{\bar{X}}) \quad \text{(Equation 2.10)}$$

Where: $z_{\alpha/2}$ represents the tabled critical two-tailed value in the normal distribution below which a proportion (percentage) equal to $[1 - (\alpha/2)]$ of the cases falls. If the proportion (percentage) of the distribution that falls within the confidence interval is subtracted from 1 (100%), it will equal the value of α .

Note that the basic difference between Equation 2.10 and Equation 2.7, is that Equation 2.10 employs a tabled critical z value instead of the corresponding t value for the same percentile. Additionally, since use of Equation 2.10 assumes that the value of σ is known, the actual value of the standard error of the population mean can be computed. Thus, $\sigma_{\bar{X}}$ is used in place of the estimated value $s_{\bar{X}}$ employed in Equation 2.7.

Generalizing from Equation 2.10, Equation 2.11 is employed to compute the 95% confidence interval for the mean of a population when the normal distribution is used.

$$CI_{.95} = \bar{X} \pm (z_{.05})(\sigma_{\bar{X}}) \quad \text{(Equation 2.11)}$$

If Equation 2.11 is employed with Example 2.1, the only value that will be different from those in Equation 2.8 is the tabled critical two-tailed value $z_{.05} = 1.96$, which is used in place of $t_{.05} = 2.26$. Since we are assuming that $\sigma = \bar{s}$, the values of $s_{\bar{X}}$ and $\sigma_{\bar{X}}$ are equivalent. Thus, $\sigma_{\bar{X}} = \sigma/\sqrt{n} = 4.25/\sqrt{10} = 1.34$.

Equation 2.11 will now be utilized to compute the 95% confidence interval for Example 2.1.

$$CI_{.95} = 7.6 \pm (1.96)(1.34) = 7.6 \pm 2.63$$

The above result can be summarized as: $4.97 \leq \mu \leq 10.23$. Thus, by using the normal distribution to compute the 95% confidence interval, the physician can be 95% confident (or the probability is .95) that the average number of visits per patient is between 4.97 and 10.23. Note

that when the normal distribution is employed with the data for Example 2.1, the range of values that defines the 95% confidence interval is smaller than the range of the values that is computed with the t distribution. This will always be the case, since, at the same level of confidence, a tabled z value will always be smaller than the corresponding tabled t value.¹⁰ As a result of this, the product resulting from multiplying the tabled value by the standard error of the population mean will be smaller when the normal distribution is employed.

If the value of σ is known, Equation 2.12 (as opposed to Equation 2.9) is used to calculate the 99% confidence interval for the mean of a population.

$$CI_{.99} = \bar{X} \pm (z_{.01})(\sigma_{\bar{X}}) \quad (\text{Equation 2.12})$$

Note that in contrast to Equation 2.9, Equation 2.12 employs the tabled critical two-tailed value $z_{.01} = 2.58$ instead of the corresponding value $t_{.01} = 3.25$. Equation 2.12 will now be used to compute the 99% confidence interval for Example 2.1.

$$CI_{.99} = 7.6 \pm (2.58)(1.34) = 7.6 \pm 3.46$$

The above result can be summarized as: $4.14 \leq \mu \leq 11.06$. Thus, by using the normal distribution to compute the 99% confidence interval, the physician can be 99% confident (or the probability is .99) that the average number of visits per patient is between 4.14 and 11.06. Note once again that the range of values obtained with Equation 2.12 (which utilizes the normal distribution) for the 99% confidence interval is smaller than the range of the values that is obtained with Equation 2.9 (which utilizes the t distribution).

Figures 2.8 and 2.9 provide a graphical summary of the computation of the 95% and 99% confidence intervals with the normal distribution.

It should be noted that even if the value of σ is known, some researchers would challenge the use of the normal distribution in the above example. The rationale for such a challenge is that, if as a result of employing a **single-sample z test**, it is determined that a significant difference exists between the hypothesized value of the population mean and \bar{X} , one can question the logic of employing the normal distribution in the computation of a confidence interval. This is the case, since, if we conclude that our sample is derived from a population with a different mean value than the hypothesized population mean, it is also possible that the population standard deviation

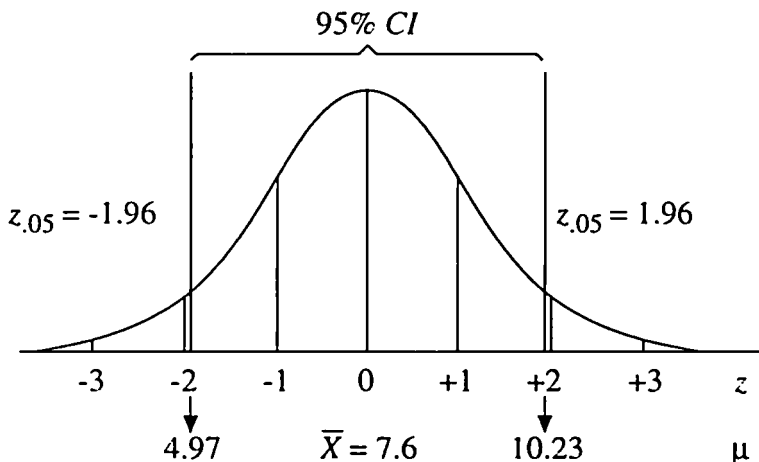


Figure 2.8 Graphical Representation of 95% Confidence Interval for Example 2.1 Through Use of the Normal Distribution

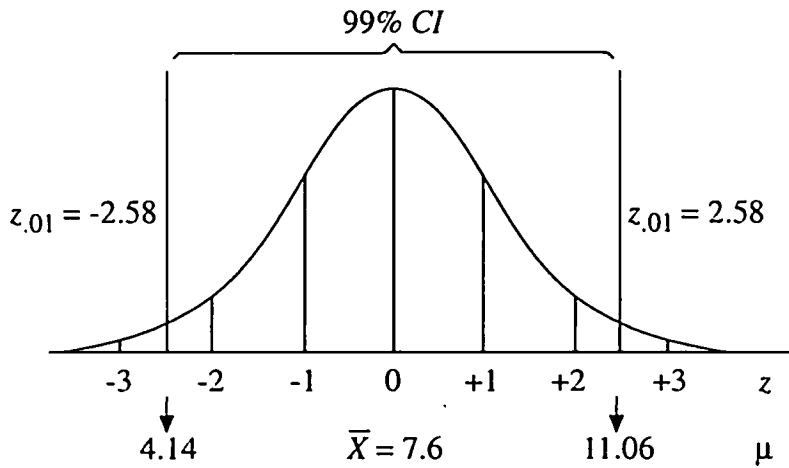


Figure 2.9 Graphical Representation of 99% Confidence Interval for Example 2.1 Through Use of the Normal Distribution

is different than the value of σ we have employed in the analysis. In such an instance, the best strategy would probably be to employ the sample data to estimate the population standard deviation. Thus, Equation 2.1 would be used to compute \bar{s} , and consequently Equations 2.8 and 2.9 (employing the t distribution) are used to compute the 95% and 99% confidence intervals.

It is worth noting that it is unlikely that a researcher will employ the normal distribution to compute a confidence interval, for the simple reason that it is improbable that one will know the value of a population standard deviation and not know the value of the population mean. For this reason most sources only illustrate confidence interval computations in reference to the t distribution.

In closing the discussion of confidence intervals, the reader should take note of the fact that the range of values which defines the 95% and 99% confidence intervals for Example 2.1 is extremely large. Because of this the researcher will not be able stipulate with great precision a single value that is likely to represent the true value of the population mean. This illustrates that a confidence interval may be quite limited in its ability to accurately estimate a population parameter, especially when the sample size upon which it is based is small. The reader should also note that the reliability of Equation 2.7 will be compromised if one or more of the assumptions of the **single-sample t test** are saliently violated.

VII. Additional Discussion of the Single-Sample t Test

Degrees of freedom The concept of **degrees of freedom**, which is frequently encountered in statistical analysis, represents the number of values in a set of data that are free to vary after certain restrictions have been placed upon the data. The concept of degrees of freedom will be illustrated through use of the following example.

Assume that one is trying to construct a set consisting of three scores which are derived from a single sample, and it is known that the mean of the sample is $\bar{X} = 5$. Under these conditions, two of the three scores that comprise the set can assume a variety of values, as long as the sum of the two scores does not exceed 15. This is the case since, if $\bar{X} = 5$ and $n = 3$, it is required that $\Sigma X = 15$. Thus, some representative values that two of the three scores may assume

are: 1 and 4; 0 and 6; 8 and 6; and 1 and 1. Note that in all four cases the sum of the two scores is less than 15. The value of the third score in all four instances is predetermined based on the values of the other two scores. Thus, if we know that two of the three scores that comprise a set are 1 and 4, the third score must equal 10, since it is the only value that will yield $\Sigma X = 15$.

The rationale for employing $df = n - 1$ in computing the degrees of freedom for the **single-sample t test** can be understood on the basis of the above discussion. Specifically, once the size of a sample is set and the mean assumes a specific value, only $n - 1$ scores will be free to vary. In the case of the **single-sample t test** (as well as a variety of other inferential statistical tests) degrees of freedom are a function of sample size. Specifically, as the sample size increases, the degrees of freedom increases. However, this is not always the case. When evaluating categorical data, degrees of freedom are generally a function of the number of categories involved in the analysis rather than the size of the sample.

Inspection of **Table A2** reveals that as degrees of freedom increase, the lower the value of the tabled critical value that the computed absolute value of t must be equal to or greater than in order to reject the null hypothesis at a given level of significance. Once again, this is not always the case. For instance, when employing the chi-square distribution (discussed later in the book) there is a direct relationship between degrees of freedom and the magnitude of the tabled critical value. In other words, as the number of degrees of freedom increases, the larger the magnitude of the tabled critical chi-square value at a given level of significance.

As noted in Section I, in actuality a separate t distribution exists for each sample size, and consequently for each degrees of freedom value. **Figure 2.10** depicts the t distribution for three different degrees of freedom values. Note that the t distribution (which is always symmetrical) closely resembles the normal distribution. As is noted in Section I, except when $n = \infty$, for a given standard deviation score, a smaller proportion of cases will fall between the mean of the t distribution and that standard deviation score than the proportion of cases that fall between the mean and that same standard deviation score in the normal distribution. As sample size (and thus degrees of freedom) increases, the shape of the t distribution becomes increasingly similar in appearance to the normal distribution, and, in fact, when $n = \infty$ becomes identical to it. As a result of this, when the sample size employed in a study is large (usually $n \geq 200$), for all practical purposes, the tabled critical values for the normal and t distributions are identical.

Inspection of the three t distributions depicted in **Figure 2.10** reveals that the lower the degrees of freedom, the larger the absolute value of t that will be required in order to reject a null

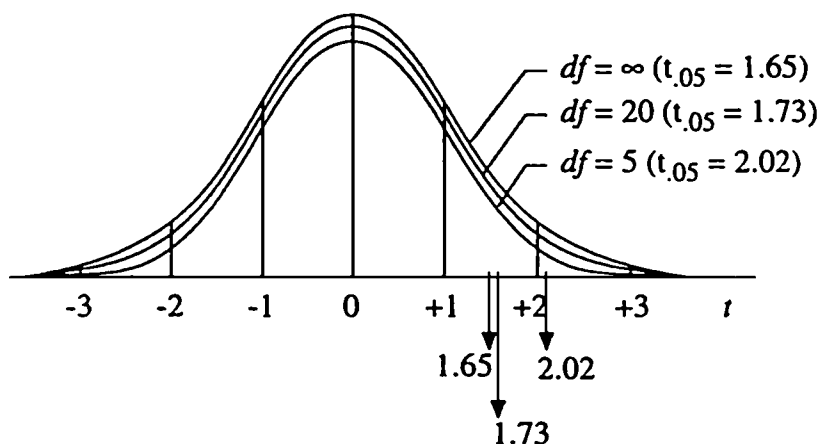


Figure 2.10. Representative t Distributions for Different df Values

hypothesis at a given level of significance. As an example, the distance between the mean and the one-tailed .05 critical t value (which corresponds to the 95th percentile of a given curve) is greatest for the $df = 5$ distribution (where $t_{.05} = 2.02$) and smallest for the $df = \infty$ distribution (where $t_{.05} = 1.65$).

Most tables of the t distribution list selected degrees of freedom values ranging from 1 through 120, and then list a final row of values for $df = \infty$. The latter set of values are identical to those in the normal distribution, since, when $df = \infty$, the two distributions are identical. As a general rule, for sample sizes substantially above 121 (which correspond to $df = 120$), the critical values for $df = \infty$ can be employed. Tables of the t distribution do not include tabled critical values for all possible degrees of freedom below 120. The protocol that is generally used if the exact df value is not listed is to either interpolate the critical value or to employ the tabled df value that is closest to it. Some sources qualify the latter by stating that one should employ the tabled df value that is closest to but not above the computed df value. The intent of this strategy is to insure that the likelihood of committing a Type I error does not exceed the prespecified alpha value.

VIII. Additional Examples Illustrating the Use of the Single-Sample t Test

If, in the case of Examples 1.1–1.4 (all of which are employed to illustrate the **single-sample z test**), a researcher does not know the value of σ and has to estimate it from the sample data, the **single-sample t test** is the appropriate test to use. The 30 scores noted in Section IV of the **single-sample z test** in reference to Example 1.1 can be employed to compute the estimated population standard deviation. Utilizing the 30 scores, the following values are computed: $\Sigma X = 222$, $\bar{X} = 7.4$, and $\Sigma X^2 = 1866$. Equations 2.1–2.3 can now be employed to conduct the necessary calculations for the **single-sample t test**. The null hypothesis that is evaluated is $H_0: \mu = 8$.

$$\begin{aligned}\tilde{s} &= \sqrt{\frac{1866 - \frac{(222)^2}{30}}{30 - 1}} = 2.77 & s_{\bar{X}} &= \frac{2.77}{\sqrt{30}} = .506 \\ t &= \frac{7.4 - 8}{.506} = -1.19\end{aligned}$$

Using the t distribution for Examples 1.1–1.4, the degrees of freedom that are employed are $df = 30 - 1 = 29$. For $df = 29$, the tabled critical two-tailed .05 and .01 values are $t_{.05} = 2.05$ and $t_{.01} = 2.76$, and the tabled critical one-tailed .05 and .01 values are $t_{.05} = 1.70$ and $t_{.01} = 2.46$. Since the computed absolute value $t = 1.19$ is less than all of the aforementioned critical values, the null hypothesis cannot be rejected. Note that when the **single-sample z test** is used to evaluate the same set of data, the directional alternative hypothesis $H_1: \mu < 8$ is supported at the .05 level. The discrepancy between the results of the two tests can be attributed to the fact that the estimated population standard deviation $\tilde{s} = 2.77$ employed for the **single-sample t test** is larger than the value $\sigma = 2$ used when the data are evaluated with the **single-sample z test**.

The **single-sample t test** cannot be employed for Examples 1.5 and 1.6 (which are also used to illustrate the **single-sample z test**), since, when $n = 1$, the estimated value of a population standard deviation will be indeterminate (since at least two scores are required to estimate a

population standard deviation). This is confirmed by the fact that no tabled critical t values are listed for zero degrees of freedom (which is the case when $n = 1$).

Example 2.2, which is based on the same data set as Example 2.1, is an additional example that can be evaluated with the **single-sample t test**.

Example 2.2. *The Sugar Snack candy company claims that each package of candy it sells contains bonus coupons (which a consumer can use toward future purchases), and that the average number of coupons per package is five. Responding to a complaint by a consumer who says the company is shortchanging people on coupons, a consumer advocate purchases 10 bags of candy from a variety of stores. The advocate counts the number of coupons in each bag and obtains the following values: 9, 10, 8, 4, 8, 3, 0, 10, 15, 9. Do the data support the claim of the complainant?*

Since the data for Example 2.2 are identical to those employed for Example 2.1, analysis with the **single-sample t test** yields the value $z = 1.94$. The value $z = 1.94$, which is consistent with the directional alternative hypothesis $H_1: \mu > 5$, is totally unexpected in view of the nature of the consumer's complaint. If anything, the researcher evaluating the data is most likely to employ either the directional alternative hypothesis $H_1: \mu < 5$ or the nondirectional alternative hypothesis $H_1: \mu \neq 5$ (neither of which are supported at the .05 level). Thus, even though the directional alternative hypothesis $H_1: \mu > 5$ is supported at the .05 level, the latter alternative hypothesis would not have been stipulated prior to collecting the data.

References

- Cohen, J. (1977). **Statistical power analysis for the behavioral sciences**. New York: Academic Press.
- Cohen, J. (1988). **Statistical power analysis for the behavioral sciences** (2nd ed.). Hillsdale, NJ: Erlbaum.
- Guenther, W. C. (1965). **Concepts of statistical inference**. New York: McGraw-Hill Book Company.

Endnotes

1. In order to be solvable, Equation 2.3 requires that there be variability in the sample. If all of the subjects in a sample have the same score, the computed value of \bar{s} will equal zero. When $\bar{s} = 0$, the value of $s_{\bar{x}}$ will always equal zero. When $s_{\bar{x}} = 0$, Equation 2.3 becomes unsolvable, thus making it impossible to compute a value for t . It is also the case that when the sample size is $n = 1$, Equation 2.1 becomes unsolvable, thus making it impossible to employ Equation 2.3 to solve for t .
2. In the event that σ is known and $n < 25$, and one elects to employ the **single-sample t test**, the value of σ should be used in computing the test statistic. Given the fact that the value of σ is known, it would be foolish to employ \bar{s} as an estimate of it.
3. The t distribution was derived by William Gossett, a British statistician who published under the pseudonym of Student.
4. It is worth noting that if the value of the population standard deviation in Example 2.1 is known to be $\sigma = 4.25$, the data can be evaluated with the **single-sample z test**. When

employed it yields the value $z = 1.94$, which is identical to the value obtained with Equation 2.3. Specifically, since $\sigma = \tilde{s} = 4.25$, $\sigma_{\bar{X}} = s_{\bar{X}} = 4.25/\sqrt{10} = 1.34$. Employing Equation 1.3 yields $z = (7.6 - 5)/1.34 = 1.94$. As is the case for the **single-sample t test**, the latter value only supports the directional alternative hypothesis $H_1: \mu > 5$ at the .05 level. This is the case since $z = 1.94$ is greater than the tabled critical one-tailed value $z_{.05} = 1.65$ in [Table A1](#). The value $z = 1.94$, which is less than the tabled critical two-tailed value $z_{.05} = 1.96$, falls just short of supporting the nondirectional alternative hypothesis $H_1: \mu \neq 5$ at the .05 level.

5. A sampling distribution of means for the t distribution when employed in the context of the **single-sample t test** is interpreted in the same manner as the sampling distribution of means for the **single-sample z test** as depicted in [Figure 1.1](#).
6. In the event the researcher is evaluating the power of the test in reference to a value of μ_1 that is less than $\mu = 5$, Distribution B will overlap the left tail of Distribution A.
7. It is really not possible to determine this value with great accuracy by interpolating the entries in [Table A2](#).
8. If the table for the normal distribution is used to estimate the power of the **single-sample t test** in this example, it can be determined that the proportion of cases that falls above a z value of 1.51 is .0655. Although the value .0655 is close to .085, it slightly underestimates the power of the test.
9. The value of δ can be computed directly through use of the following equation: $\delta = (\mu_1 - \mu)/(\sigma/\sqrt{n})$. Note that the equation expresses effect size in standard deviation units of the sampling distribution.
10. As noted in Section V, the only exception to this will be when the sample size is extremely large, in which case the normal and t distributions are identical. Under such conditions the appropriate values for z and t employed in the confidence interval equation will be identical.

Test 3

The Single-Sample Chi-Square Test for a Population Variance (Parametric Test Employed with Interval/Ratio Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test Does a sample of n subjects (or objects) come from a population in which the variance (σ^2) equals a specified value?

Relevant background information on test The **single-sample chi-square test for a population variance** is employed in a hypothesis testing situation involving a single sample in order to determine whether or not a sample with an estimated population variance of \hat{s}^2 is derived from a population with a variance of σ^2 . If the result of the test is significant, the researcher can conclude there is a high likelihood the sample is derived from a population in which the variance is some value other than σ^2 . The **single-sample chi-square test for a population variance** is based on the chi-square distribution. The test statistic is represented by the notation χ^2 (where χ represents the lower case Greek letter **chi**).

The **single-sample chi-square test for a population variance** is used with interval/ratio level data and is based on the following assumptions: a) The distribution of data in the underlying population from which the sample is derived is normal; and b) The sample has been randomly selected from the population it represents. If either of the assumptions is saliently violated, the reliability of the test statistic may be compromised.¹

The chi-square distribution is a continuous asymmetrical theoretical probability distribution. A chi-square value must fall within the range $0 \leq \chi^2 \leq \infty$, and thus (unlike values for the normal and t distributions) can never be a negative number. As is the case with the t distribution, there are an infinite number of chi-square distributions — each distribution being a function of the number of degrees of freedom employed in an analysis. Figure 3.1 depicts the chi-square distribution for three different degrees of freedom values. Inspection of the three distributions reveals:

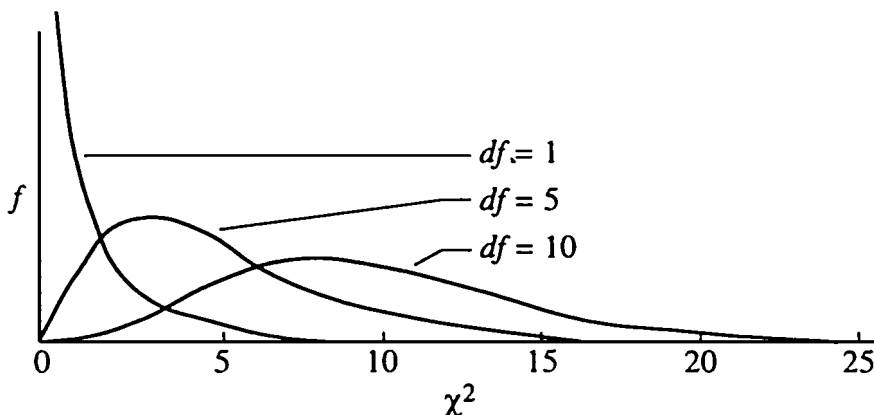


Figure 3.1 Representative Chi-Square Distributions for Different df Values

a) The lower the degrees of freedom, the more positively skewed the distribution (i.e., the larger the proportion of scores at the lower end of the distribution); and b) The greater the degrees of freedom, the more symmetrical the distribution. A thorough discussion of the chi-square distribution can be found in Section V.

II. Example

Example 3.1 *The literature published by a company that manufactures hearing aid batteries claims that a certain model battery has an average life of 7 hours ($\mu = 7$) and a variance of 5 hours ($\sigma^2 = 5$). A customer who uses the hearing aid battery believes that the value stated in the literature for the variance is too low. In order to test his hypothesis the customer records the following times (in hours) for ten batteries he purchases during the month of September: 5, 6, 4, 3, 11, 12, 9, 13, 6, 8. Do the data indicate that the variance for battery time is some value other than 5?*

III. Null versus Alternative Hypotheses

Null hypothesis $H_0: \sigma^2 = 5$

(The variance of the population the sample represents equals 5.)

Alternative hypothesis $H_0: \sigma^2 \neq 5$

(The variance of the population the sample represents does not equal 5. This is a **nondirectional alternative hypothesis**, and it is evaluated with a **two-tailed test**. In order to be supported, the obtained chi-square value must be equal to or greater than the tabled critical two-tailed chi-square value at the prespecified level of significance in the upper tail of the chi-square distribution, or equal to or less than the tabled critical two-tailed chi-square value at the prespecified level of significance in the lower tail of the chi-square distribution. A full explanation of the protocol for interpreting chi-square values within the framework of the **single-sample chi-square test for a population variance** can be found in Section V.)

or

$$H_0: \sigma^2 > 5$$

(The variance of the population the sample represents is greater than 5. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. In order to be supported, the obtained chi-square value must be equal to or greater than the tabled critical one-tailed chi-square value at the prespecified level of significance in the upper tail of the chi-square distribution.)

or

$$H_0: \sigma^2 < 5$$

(The variance of the population the sample represents is less than 5. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. In order to be supported, the obtained chi-square value must be equal to or less than the tabled critical one-tailed chi-square value at the prespecified level of significance in the lower tail of the chi-square distribution.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis is rejected.²

IV. Test Computations

Table 3.1 summarizes the data for Example 3.1.

Table 3.1 Summary of Data for Example 3.1		
Battery	X	X^2
1	5	25
2	6	36
3	4	16
4	3	9
5	11	121
6	12	144
7	9	81
8	13	169
9	6	36
10	8	64
$\Sigma X = 77$		$\Sigma X^2 = 701$

In order to compute the test statistic for the **single-sample chi-square test for a population variance**, it is necessary to use the sample data to calculate an unbiased estimate of the population variance. \tilde{s}^2 , the unbiased estimate of σ^2 , is computed with Equation 3.1 (which is the same as Equation I.5 in the **Introduction**).

$$\tilde{s}^2 = \frac{\Sigma X^2 - \frac{(\Sigma X)^2}{n}}{n - 1} \quad (\text{Equation 3.1})$$

Employing Equation 3.1, the value $\tilde{s}^2 = 12.01$ is computed.

$$\tilde{s}^2 = \frac{701 - \frac{(77)^2}{10}}{10 - 1} = 12.01$$

Equation 3.2 is the test statistic for the **single-sample chi-square test for a population variance**.

$$\chi^2 = \frac{(n - 1) \tilde{s}^2}{\sigma^2} \quad (\text{Equation 3.2})$$

Employing the values $n = 10$, $\tilde{s}^2 = 12.01$, and $\sigma^2 = 5$ (which is the hypothesized value of σ^2 stated in the null hypothesis), Equation 3.2 is employed to compute the value $\chi^2 = 21.62$.

$$\chi^2 = \frac{(10 - 1)(12.01)}{5} = 21.62$$

V. Interpretation of the Test Results

The computed value $\chi^2 = 21.62$ is evaluated with **Table A4 (Table of the Chi-Square Distribution)** in the **Appendix**. In **Table A4**, chi-square values are listed in relation to the proportion of cases (which are recorded at the top of each column) that falls below a tabled χ^2

value in the sampling distribution, and the number of **degrees of freedom** (which are recorded in the left-hand column of each row).³ Equation 3.3 is employed to compute the degrees of freedom for the **single-sample chi-square test for a population variance**.

$$df = n - 1 \quad \text{(Equation 3.3)}$$

Employing Equation 3.3, we compute that $df = 10 - 1 = 9$. For $df = 9$, the tabled critical two-tailed .05 values are $\chi^2_{.025} = 2.70$ and $\chi^2_{.975} = 19.02$. These values are the tabled critical two-tailed .05 values, since the proportion of the distribution that falls between $\chi^2 = 0$ and $\chi^2_{.025} = 2.70$ is .025, and the proportion of the distribution that falls above $\chi^2_{.975} = 19.02$ is .025. Thus, the extreme 5% of the distribution is comprised of chi-square values that fall below $\chi^2_{.025} = 2.70$ and above $\chi^2_{.975} = 19.02$. In the same respect, the tabled critical two-tailed .01 values are $\chi^2_{.005} = 1.73$ and $\chi^2_{.995} = 23.59$. These values are the tabled critical two-tailed .01 values, since the proportion of the distribution that falls between $\chi^2 = 0$ and $\chi^2_{.005} = 1.73$ is .005, and the proportion of the distribution that falls above $\chi^2_{.995} = 23.59$ is .005. Thus, the extreme 1% of the distribution is comprised of chi-square values that fall below $\chi^2_{.005} = 1.73$ and above $\chi^2_{.995} = 23.59$.

For $df = 9$, the tabled critical one-tailed .05 values are $\chi^2_{.05} = 3.33$ and $\chi^2_{.95} = 16.92$. These values are the tabled critical one-tailed .05 values, since the proportion of the distribution that falls between $\chi^2 = 0$ and $\chi^2_{.05} = 3.33$ is .05, and the proportion of the distribution that falls above $\chi^2_{.95} = 16.92$ is .05. In the same respect, the tabled critical one-tailed .01 values are $\chi^2_{.01} = 2.09$ and $\chi^2_{.99} = 21.67$. These values are the tabled critical one-tailed .01 values, since the proportion of the distribution that falls between $\chi^2 = 0$ and $\chi^2_{.01} = 2.09$ is .01, and the proportion of the distribution that falls above $\chi^2_{.99} = 21.67$ is .01.

Figures 3.2 and 3.3 depict the tabled critical .05 and .01 values for the chi-square sampling distribution when $df = 9$. The mean of a chi-square sampling distribution will always equal the degrees of freedom for the distribution. Thus, $\mu_{\chi^2} = df = n - 1$. The standard deviation of the sampling distribution will always be $\sigma_{\chi^2} = \sqrt{2df}$. Consequently, the variance will be $\sigma_{\chi^2}^2 = 2df$. In the case of Example 3.1 where $df = 9$, $\mu_{\chi^2} = 9$ and $\sigma_{\chi^2}^2 = 18$.

The following guidelines are employed in evaluating the null hypothesis for the **single-sample chi-square test for a population variance**.

a) If the alternative hypothesis employed is nondirectional, the null hypothesis can be rejected if the obtained chi-square value is equal to or greater than the tabled critical two-tailed chi-square value at the prespecified level of significance in the upper tail of the chi-square distribution, or equal to or less than the tabled critical two-tailed chi-square value at the prespecified level of significance in the lower tail of the chi-square distribution.⁴

b) If the alternative hypothesis employed is directional and predicts a population variance larger than the value stated in the null hypothesis, the null hypothesis can only be rejected if the obtained chi-square value is equal to or greater than the tabled critical one-tailed chi-square value at the prespecified level of significance in the upper tail of the chi-square distribution.

c) If the alternative hypothesis employed is directional and predicts a population variance smaller than the value stated in the null hypothesis, the null hypothesis can only be rejected if the obtained chi-square value is equal to or less than the tabled critical one-tailed chi-square value at the prespecified level of significance in the lower tail of the chi-square distribution.

Employing the above guidelines, we can conclude the following.

The nondirectional alternative hypothesis $H_1: \sigma^2 \neq 5$ is supported at the .05 level. This is the case since the obtained value $\chi^2 = 21.62$ is greater than the tabled critical two-tailed

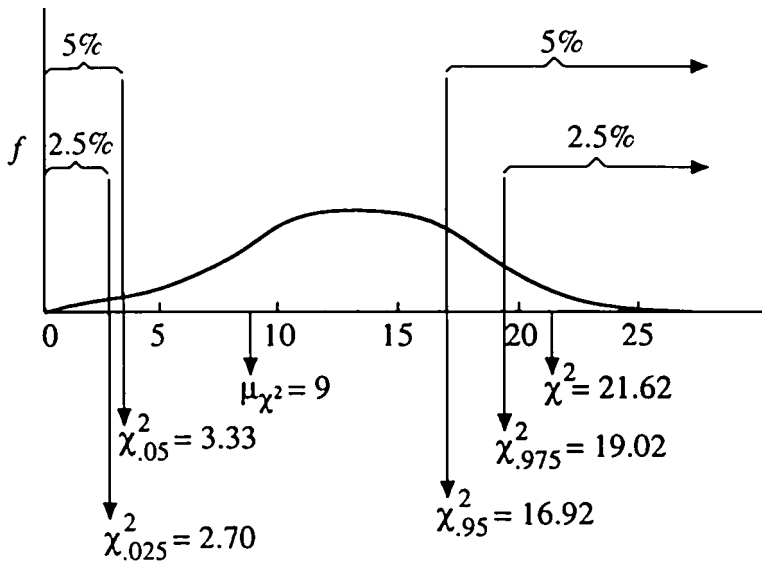


Figure 3.2 Tabled Critical Two-Tailed and One-Tailed .05 χ^2 Values for $df = 9$

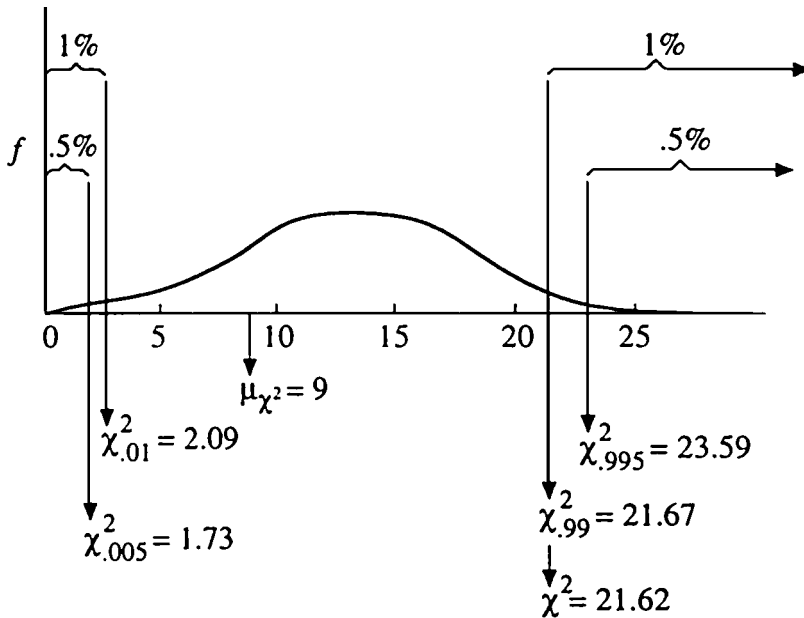


Figure 3.3 Tabled Critical Two-Tailed and One-Tailed .01 χ^2 Values for $df = 9$

.05 value $\chi^2_{.975} = 19.02$ in the upper tail of the distribution. The nondirectional alternative hypothesis $H_1: \sigma^2 \neq 5$ is not supported at the .01 level, since $\chi^2 = 21.62$ is less than the tabled critical two-tailed .01 value $\chi^2_{.995} = 23.59$ in the upper tail of the distribution.

The directional alternative hypothesis $H_1: \sigma^2 > 5$ is supported at the .05 level. This is the case since the obtained value $\chi^2 = 21.62$ is greater than the tabled critical one-tailed .05 value $\chi^2_{.95} = 16.92$ in the upper tail of the distribution. The directional alternative hypothesis $H_1: \sigma^2 > 5$ is not supported at the .01 level, since $\chi^2 = 21.62$ is less than the tabled critical one-tailed .01 value $\chi^2_{.99} = 21.67$ in the upper tail of the distribution. Note that in order for the data to be consistent with the directional alternative hypothesis $H_1: \sigma^2 > 5$, the computed value of \hat{s}^2 must be greater than the value $\sigma^2 = 5$ stated in the null hypothesis.

The directional alternative hypothesis $H_1: \sigma^2 < 5$ is not supported. This is the case since

in order for the latter alternative hypothesis to be supported, the obtained chi-square value must be equal to or less than the tabled critical one-tailed .05 value $\chi^2_{.05} = 3.33$ in the lower tail of the distribution. If $\alpha = .01$ is employed, in order for the directional alternative hypothesis $H_1: \sigma^2 < 5$ to be supported, the obtained chi-square value must be equal to or less than the tabled critical one-tailed value $\chi^2_{.01} = 2.09$ in the lower tail of the distribution. In order for the data to be consistent with the alternative hypothesis $H_1: \sigma^2 < 5$, the computed value of \hat{s}^2 must be less than the value $\sigma^2 = 5$ stated in the null hypothesis.

A summary of the analysis of Example 3.1 with the **single-sample chi-square test for a population variance** follows: We can conclude that it is unlikely that the sample of 10 batteries comes from a population with a variance equal to 5. The data suggest that the variance of the population is greater than 5. This result can be summarized as follows: $\chi^2(9) = 21.62, p < .05$.

Although it is not required in order to evaluate the null hypothesis $H_0: \sigma^2 = 5$, through use of Equations 1.1/1.1 it can be determined that the mean number of hours the 10 batteries functioned is $\bar{X} = \Sigma X/n = 77/10 = 7.7$. The latter value is greater than $\mu = 7$, which is the mean number of hours claimed in the company's literature. If the researcher wants to determine whether the value $\bar{X} = 7.7$ is significantly larger than the value $\mu = 7$, it can be argued that one should employ the **single-sample t test (Test 2)** for the analysis. The rationale for employing the latter test is that if the null hypothesis $H_0: \sigma^2 = 5$ is rejected, the researcher is concluding that the true value of the population variance is unknown, and consequently, the latter value should be estimated from the sample data. If, on the other hand, one does not employ the **single-sample chi-square test for a population variance** to evaluate the null hypothesis $H_0: \sigma^2 = 5$ (and is thus unaware of the fact that the data are not consistent with the latter null hypothesis), one will assume $\sigma^2 = 5$ and employ the **single-sample z test (Test 1)** to evaluate the null hypothesis $H_0: \mu = 7$ (since the latter test is employed when the value of σ^2 is known).

VI. Additional Analytical Procedures for the Single-Sample Chi-Square Test for a Population Variance and/or Related Tests

1. Large sample normal approximation of the chi-square distribution When the sample size is larger than 30, the normal distribution can be employed to approximate the test statistic for the **single-sample chi-square test for a population variance**. Equation 3.4 is employed to compute the normal approximation.

$$z = \frac{\frac{\hat{s}^2 - \sigma^2}{\sigma^2}}{\frac{1}{\sqrt{2n}}} \quad \text{(Equation 3.4)}$$

To illustrate the use of Equation 3.4, let us assume that in Example 3.1 the computed value $\hat{s}^2 = 12.01$ is based on a sample size of $n = 30$. Employing Equation 3.2, the value $\chi^2 = 69.66$ is computed.

$$\chi^2 = \frac{(30 - 1)(12.01)}{5} = 69.66$$

Employing **Table A4**, for $df = 30 - 1 = 29$, the tabled critical two-tailed .05 and .01 values in the upper tail of the chi-square distribution are $\chi^2_{.975} = 45.72$ and $\chi^2_{.995} = 52.34$, and the tabled critical one-tailed .05 and .01 values in the upper tail of the distribution are $\chi^2_{.95} = 42.56$ and $\chi^2_{.99} = 49.59$. Since the obtained value $\chi^2 = 69.66$ is greater than all of the aforementioned critical values, the nondirectional alternative hypothesis $H_1: \sigma^2 \neq 5$ and the

directional alternative hypothesis $H_1: \sigma^2 > 5$ are supported at both the .05 and .01 levels.

Equation 3.4 will now be employed to evaluate the data for Example 3.1, if $n = 30$. Since $\sigma^2 = 5$ and $\bar{s}^2 = 12.01$, it follows that $\sigma = 2.24$ and $\bar{s} = 3.47$. These values are substituted in Equation 3.4.

$$z = \frac{3.47 - 2.24}{\frac{2.24}{\sqrt{(2)(30)}}} = 4.24$$

Employing **Table A1 (Table of the Normal Distribution)** in the **Appendix**, we determine that the tabled critical two-tailed .05 and .01 values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed .05 and .01 values are $z_{.05} = 1.65$ and $z_{.01} = 2.33$. Since the obtained value $z = 4.24$ is greater than all of the aforementioned critical values, the nondirectional alternative hypothesis $H_1: \sigma^2 \neq 5$ and the directional alternative hypothesis $H_1: \sigma^2 > 5$ are supported at both the .05 or .01 levels. The conclusions derived through use of the normal approximation are identical to those reached with Equation 3.2.

If Equation 3.4 is employed with Example 3.1 for $n = 10$, it results in the value $z = 2.46$. Specifically: $z = [3.47 - 2.24] / [2.24/\sqrt{(2)(10)}] = 2.46$. Since the latter value is greater than the tabled critical two-tailed value $z_{.05} = 1.96$ and the tabled critical one-tailed values $z_{.05} = 1.65$ and $z_{.01} = 2.33$, the nondirectional alternative hypothesis $H_1: \sigma^2 \neq 5$ is supported at the .05 level and the directional alternative hypothesis $H_1: \sigma^2 > 5$ is supported at both the .05 and .01 levels. Recollect that when Equation 3.2 is employed with Example 3.1, the nondirectional alternative hypothesis $H_1: \sigma^2 \neq 5$ and the directional alternative hypothesis $H_1: \sigma^2 > 5$ are both supported, but only at the .05 level. Thus, when the normal approximation is employed with a small sample size, it appears to inflate the likelihood of committing a Type I error (since the normal approximation supports the nondirectional alternative hypothesis $H_1: \sigma^2 > 5$ at the .01 level).

2. Computation of a confidence interval for the variance of a population represented by a sample An equation for computing a confidence interval for the variance of a population (as well as the population standard deviation) can be derived by algebraically transposing the terms in Equation 3.2. As is noted in the discussion of the **single-sample *t* test**, a confidence interval is a range of values within which a researcher can be confident to a specified degree that the true value of a population parameter falls. Stated probabilistically, a confidence interval identifies the range of values for which there is a specific likelihood that the population parameter falls within. Equation 3.5 is the general equation for computing a confidence interval for a population variance.

$$\frac{(n - 1) \bar{s}^2}{\chi_{[1 - (\alpha/2)]}^2} \leq \sigma^2 \leq \frac{(n - 1) \bar{s}^2}{\chi_{(\alpha/2)}^2} \quad \text{(Equation 3.5)}$$

Where: $\chi_{(\alpha/2)}^2$ is the tabled critical two-tailed value in the chi-square distribution below which a proportion (percentage) equal to $[1 - (\alpha/2)]$ of the cases falls. If the proportion (percentage) of the distribution that falls within the confidence interval is subtracted from 1 (100%), it will equal the value of α .

Equations 3.6 and 3.7 are employed to compute the 95% and 99% confidence intervals for a population variance. The critical values employed in Equation 3.6 demarcate the middle 95% of the chi-square distribution, while the critical values employed in Equation 3.7 demarcate the

middle 99% of the distribution.

$$\frac{(n - 1) \bar{s}^2}{\chi_{.975}^2} \leq \sigma^2 \leq \frac{(n - 1) \bar{s}^2}{\chi_{.025}^2} \quad \text{(Equation 3.6)}$$

$$\frac{(n - 1) \bar{s}^2}{\chi_{.995}^2} \leq \sigma^2 \leq \frac{(n - 1) \bar{s}^2}{\chi_{.005}^2} \quad \text{(Equation 3.7)}$$

Using the data for Example 3.1, Equation 3.6 is employed to compute the 95% confidence interval for the population variance.

$$\frac{(10 - 1) (12.01)}{19.02} \leq \sigma^2 \leq \frac{(10 - 1) (12.01)}{2.70}$$

$$5.68 \leq \sigma^2 \leq 40.03$$

Thus, we can be 95% confident (or the probability is .95) that the true value of the variance of the population the sample represents falls between the values 5.68 and 40.03. By taking the square root of the latter values, we can determine the 95% confidence interval for the population standard deviation. Thus, $2.38 \leq \sigma \leq 6.33$. In other words, we can be 95% confident (or the probability is .95) that the true value of the standard deviation of the population the sample represents falls between the values 2.38 and 6.33.

Equation 3.7 is employed below to compute the 99% confidence interval.

$$\frac{(10 - 1) (12.01)}{23.59} \leq \sigma^2 \leq \frac{(10 - 1) (12.01)}{1.73}$$

$$4.58 \leq \sigma^2 \leq 62.48$$

Thus, we can be 99% confident (or the probability is .99) that the true value of the variance of the population the sample represents falls between the values 4.58 and 62.48. By taking the square root of the latter values, we can determine the 99% confidence interval for the population standard deviation. Thus, $2.14 \leq \sigma \leq 7.90$. In other words, we can be 99% confident (or the probability is .99) that the true value of the standard deviation of the population the sample represents falls between the values 2.14 and 7.90. Note that (as is the case for confidence intervals for a population mean) a larger range of values defines the 99% confidence interval for a population variance than the 95% confidence interval.

When $n \geq 30$, the normal distribution can be employed to approximate the confidence interval for a population standard deviation. Equation 3.8 is the general equation for computing a confidence interval using the normal approximation.

$$\frac{\bar{s}}{1 + \frac{z_{(\alpha/2)}}{\sqrt{2n}}} \leq \sigma \leq \frac{\bar{s}}{1 - \frac{z_{(\alpha/2)}}{\sqrt{2n}}} \quad \text{(Equation 3.8)}$$

Where: $z_{(\alpha/2)}$ is the tabled critical two-tailed value in the normal distribution below which a proportion (percentage) equal to $[1 - (\alpha/2)]$ of the cases falls. If the proportion (percentage) of the distribution that falls within the confidence interval is subtracted from 1 (100%), it will equal the value of α .

Equations 3.9 and 3.10 employ the normal approximation to compute the 95% and 99% confidence intervals for a population standard deviation. The values $z_{.05}$ and $z_{.01}$ used in the latter equations are the tabled critical two-tailed .05 and .01 values $z_{.05} = 1.96$ and $z_{.01} = 2.58$. By squaring a value obtained for the confidence interval for a population standard deviation, one can determine the confidence interval for the population variance.

$$\frac{\bar{s}}{1 + \frac{z_{.05}}{\sqrt{2n}}} \leq \sigma \leq \frac{\bar{s}}{1 - \frac{z_{.05}}{\sqrt{2n}}} \quad (\text{Equation 3.9})$$

$$\frac{\bar{s}}{1 + \frac{z_{.01}}{\sqrt{2n}}} \leq \sigma \leq \frac{\bar{s}}{1 - \frac{z_{.01}}{\sqrt{2n}}} \quad (\text{Equation 3.10})$$

For purposes of illustration, let us assume that $n = 30$ in Example 3.1. Using $n = 30$ and $\bar{s}^2 = 12.01$ for Example 3.1, Equation 3.9 is employed to compute the 95% confidence interval for the population standard deviation and variance.

$$\begin{aligned} \frac{3.47}{1 + \frac{1.96}{\sqrt{(2)(30)}}} &\leq \sigma \leq \frac{3.47}{1 - \frac{1.96}{\sqrt{(2)(30)}}} \\ 2.77 &\leq \sigma \leq 4.65 \\ 7.67 &\leq \sigma^2 \leq 21.62 \end{aligned}$$

Using $n = 30$ and $\bar{s}^2 = 12.01$ for Example 3.1, Equation 3.10 is employed to compute the 99% confidence interval for the population standard deviation and variance.

$$\begin{aligned} \frac{3.47}{1 + \frac{2.58}{\sqrt{(2)(30)}}} &\leq \sigma \leq \frac{3.47}{1 - \frac{2.58}{\sqrt{(2)(30)}}} \\ 2.61 &\leq \sigma \leq 5.18 \\ 6.81 &\leq \sigma^2 \leq 26.83 \end{aligned}$$

If Equations 3.6 and 3.7 are employed with Example 3.1 for $n = 30$ and $\bar{s}^2 = 12.01$, they yield values close to those obtained with Equations 3.9 and 3.10. As the size of the sample increases, the values that define a confidence interval based on the use of the normal versus chi-square distributions converge, and for large sample sizes the two distributions yield the same values.

Equation 3.6 is employed to compute the 95% confidence interval. Note that for $df = 29$, the tabled critical values $\chi_{.025}^2 = 16.05$ and $\chi_{.975}^2 = 45.72$ are employed in Equation 3.6.

$$\begin{aligned} \frac{(30 - 1)(12.01)}{45.72} &\leq \sigma^2 \leq \frac{(30 - 1)(12.01)}{16.05} \\ 7.62 &\leq \sigma^2 \leq 21.70 \\ 2.76 &\leq \sigma \leq 4.66 \end{aligned}$$

Equation 3.7 is employed to compute the 99% confidence interval. Note that for $df = 29$, the tabled critical values $\chi^2_{.005} = 13.21$ and $\chi^2_{.995} = 52.34$ are employed in Equation 3.7.

$$\frac{(30 - 1) (12.01)}{52.34} \leq \sigma^2 \leq \frac{(30 - 1) (12.01)}{13.21}$$

$$6.65 \leq \sigma^2 \leq 26.37$$

$$2.58 \leq \sigma \leq 5.13$$

In closing the discussion of confidence intervals, the reader should take note of the fact that the range of values which defines the 95% and 99% confidence intervals for Example 3.1 is extremely large. Because of this the researcher will not be able stipulate with great precision a single value that is likely to represent the true value of the population variance/standard deviation. This illustrates that a confidence interval may be quite limited in its ability to accurately estimate a population parameter, especially when the sample size upon which it is based is small.⁵ The reader should also take note of the fact that the reliability of Equations 3.5 and 3.8 will be compromised if one or more of the assumptions of the **single-sample chi-square test for a population variance** is saliently violated.

3. Sources for computing the power of the single-sample chi-square test for a population variance Although it will not be described in this book, the protocol for computing the power of the **single-sample chi-square test for a population variance** is described in Guenther (1965) (who provides computational guidelines and graphs for quick power computations) and Zar (1999).

VII. Additional Discussion of the Single-Sample Chi-Square Test for a Population Variance

No additional material will be discussed in this section.

VIII. Additional Examples Illustrating the Use of the Single-Sample Chi-Square Test for a Population Variance

With the exception of Examples 1.5 and 1.6, the **single-sample chi-square test for a population variance** can be employed to test a hypothesis about a population variance (or standard deviation) with any of the examples that are employed to illustrate the **single-sample z test** (Examples 1.1–1.4) and the **single-sample t test** (Examples 2.1 and 2.2).

Examples 3.2–3.5 are four additional examples that can be evaluated with the **single-sample chi-square test for a population variance**. Since these examples employ the same population parameters and sample data used in Example 3.1, they yield the same result. The reader should take note of the fact that although in Examples 3.4 and 3.5 the value $\sigma = 2.24$ is given for the population standard deviation, when the latter value is squared, it results in $\sigma^2 = 5$. A different set of data are employed in Example 3.6, which is the last example presented in this section.

Example 3.2 *A manufacturer of a machine that makes ball bearings claims that the variance of the diameter of the ball bearings produced by the machine is 5 millimeters. A company that has purchased the machine measures the diameter of a random sample of ten ball bearings. The computed estimated population variance of the diameters of ten ball bearings is 12.01 millimeters. Is the obtained value $\tilde{s}^2 = 12.01$ consistent with the null hypothesis $H_0: \sigma^2 = 5$?*

Example 3.3 A meteorologist develops a theory which predicts a variance of five degrees for the temperature recorded at noon each day in a canyon situated within a mountain range 100 miles east of the South Pole. Over a ten-day period the following temperatures are recorded: 5, 6, 4, 3, 11, 12, 9, 13, 6, 8. Do the data support the meteorologist's theory?

Example 3.4 A chemical company claims that the standard deviation for the number of tons of waste it discards annually is $\sigma = 2.24$. Assume that during a ten-year period the following annual values are recorded for the number of tons of waste discarded: 5, 6, 4, 3, 11, 12, 9, 13, 6, 8. Are the data consistent with the company's claim?

Example 3.5 During more than three decades of teaching, a college professor determines that the mean and standard deviation on a chemistry final examination are respectively 7 and 2.24. During the fall semester of a year in which he employs a new teaching method, ten students who take the final examination obtain the following scores: 5, 6, 4, 3, 11, 12, 9, 13, 6, 8. Do the data suggest that the new teaching method results in an increase in variability in performance?

Example 3.6 A pharmaceutical company claims that upon ingesting its cough medicine a person ceases to cough almost immediately. The company claims that the standard deviation of the number of coughs emitted by a person after ingesting the medicine is 5. In order to evaluate the company's claim, a physician evaluates a random sample of ten patients who come into his office coughing excessively. The physician records the following number of coughs emitted by each of the patients after he is given a therapeutic dosage of the medicine: 9, 10, 8, 4, 8, 3, 0, 10, 15, 9. Is the variability of the data consistent with the company's claim for the product?

The data for Example 3.6 are identical to those employed for Example 2.1, which is used to illustrate the **single-sample t test**. In the computations for the latter test, through use of Equation 2.1, it is determined that the estimated population standard deviation for the data is $\bar{s} = 4.25$. Since the population variance is the square of the standard deviation, we can determine that $\sigma^2 = (5)^2 = 25$ and $\bar{s}^2 = (4.25)^2 = 18.06$. Since the company claims that the population standard deviation is 5, the null hypothesis for Example 3.6 can be stated as either $H_0: \sigma = 5$ or $H_0: \sigma^2 = 25$. The nondirectional and directional alternative hypotheses (stated in reference to $H_0: \sigma = 5$) that can be employed for Example 3.6 are as follows: $H_1: \sigma \neq 5$; $H_1: \sigma > 5$; and $H_1: \sigma < 5$. When Equation 3.2 is employed to evaluate the null hypothesis $H_0: \sigma = 5$, the value $\chi^2 = 6.50$ is computed.

$$\chi^2 = \frac{(10 - 1)(18.06)}{25} = 6.50$$

Since $n = 10$, the tabled critical values for $df = 9$ are employed to evaluate the computed value $\chi^2 = 6.50$. Since the latter value is less than the tabled critical two-tailed .05 value $\chi^2_{.975} = 19.02$ in the upper tail of the chi-square distribution and greater than the tabled critical two-tailed .05 value $\chi^2_{.025} = 2.70$ in the lower tail of the distribution, the nondirectional alternative hypothesis $H_1: \sigma \neq 5$ is not supported. Since $\chi^2 = 6.50$ is less than the tabled critical one-tailed .05 value $\chi^2_{.95} = 16.92$ in the upper tail of the distribution, the directional alternative hypothesis $H_1: \sigma > 5$ is not supported. Since $\chi^2 = 6.50$ is greater than the tabled critical one-tailed .05 value $\chi^2_{.05} = 3.33$ in the lower tail of the distribution, the directional alternative hypothesis $H_1: \sigma < 5$ is not supported. Thus, regardless of which alternative hypothesis one employs, the data do not contradict the company's statement that the population standard deviation is $\sigma = 5$.

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Endnotes

1. Most sources note that violation of the normality assumption is much more serious for the **single-sample chi-square test for a population variance** than it is for tests concerning the mean of a single sample (i.e., the **single-sample z test** and the **single-sample t test**). Especially in the case of small sample sizes, violation of the normality assumption can severely compromise the accuracy of the tabled values employed to evaluate the chi-square statistic.
2. One can also state the null and alternative hypotheses in reference to the population standard deviation (which is the square root of the population variance). Since in Example 3.1 $\sigma = \sqrt{\sigma^2} = \sqrt{5} = 2.24$, one can state the null hypothesis and nondirectional and directional alternative hypotheses as follows: $H_0: \sigma = 2.24$; $H_1: \sigma \neq 2.24$; $H_1: \sigma > 2.24$; and $H_1: \sigma < 2.24$.
3. The use of the chi-square distribution in evaluating the variance is based on the fact that for any value of n , the sampling distribution of \bar{s}^2 has a direct linear relationship to the chi-square distribution for $df = n - 1$. As is the case for the chi-square distribution, the sampling distribution of \bar{s}^2 is positively skewed. Although the average of the sampling distribution for \bar{s}^2 will equal σ^2 , because of the positive skew of the distribution, a value of \bar{s}^2 is more likely to underestimate rather than overestimate the value of σ^2 .
4. When the chi-square distribution is employed within the framework of the **single-sample chi-square test for a population variance**, it is common practice to employ critical values derived from both tails of the distribution. However, when the chi-square distribution is used with other statistical tests, one generally employs critical values that are only derived from the right tail of the distribution. Examples of chi-square tests which generally only employ the right tail of the distribution are the **chi-square goodness-of-fit test (Test 8)** and the **chi-square test for $r \times c$ tables (Test 16)**.
5. Although the procedure described in this section for computing a confidence interval for a population variance is the one that is most commonly described in statistics books, it does not result in the shortest possible confidence interval that can be computed. Hogg and Tanis (1988) describe a method (based on Crisman (1975)) requiring more advanced mathematical procedures that allows one to compute the shortest possible confidence interval for a population variance. For large sample sizes the difference between the latter method and the method described in this section will be trivial.

Test 4

The Single-Sample Test for Evaluating Population Skewness

(Parametric Test Employed with Interval/Ratio Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test Does a sample of n subjects (or objects) come from a population distribution that is symmetrical (i.e., not skewed)?

Relevant background information on test Prior to reading this section the reader should review the discussion of **skewness** in the **Introduction**. As noted in the **Introduction**, skewness is a measure reflecting the degree to which a distribution is asymmetrical. From a statistical perspective, the skewness of a distribution represents the **third moment about the mean** (m_3), which is represented by Equation 4.1 (which is identical to Equation 1.14).

$$m_3 = \frac{\sum(X - \bar{X})^3}{n} \quad \text{(Equation 4.1)}$$

Skewness can be employed as a criterion for determining the **goodness-of-fit** of data with respect to a normal distribution. Various sources (e.g., D'Agostino (1970, 1986), D'Agostino and Stephens (1986), D'Agostino *et al.* (1990)) state that in spite of the fact that it is not as commonly employed as certain alternative goodness-of-fit tests, the **single-sample test for evaluating population skewness** provides an excellent test for evaluating a hypothesis of goodness-of-fit for normality, when it is employed in conjunction with the result of the **single-sample test for evaluating population kurtosis** (Test 5). The results of the latter two tests are employed in the **D'Agostino–Pearson test of normality** (Test 5a), which is described in Section VI of the **single-sample test for evaluating population kurtosis**. D'Agostino (1986), D'Agostino *et al.* (1990) and Zar (1999) state that the **D'Agostino–Pearson test of normality** provides for a more powerful test of the normality hypothesis than does either the **Kolmogorov–Smirnov goodness-of-fit test for a single sample** (Test 7) or the **chi-square goodness-of-fit test** (Test 8) (both of which are described later in the book). D'Agostino *et al.* (1990) state that because of their lack of power, the latter two tests should not be employed for assessing normality. Other sources, however, take a more favorable attitude towards the **Kolmogorov–Smirnov goodness-of-fit test for a single sample** and the **chi-square goodness-of-fit test** as tests of goodness-of-fit for normality (e.g., Conover (1980, 1999), Daniel (1990), Hollander and Wolfe (1999), Marascuilo and McSweeney (1977), Siegel and Castellan (1988), and Sprent (1993)).

In the **Introduction** it was noted that since the value computed for m_3 is in cubed units, it is often converted into the unitless statistic g_1 . The latter, which is an estimate of the population parameter γ_1 (where γ represents the lower case Greek letter **gamma**), is commonly employed to express skewness. When a distribution is symmetrical (about the mean), the value of g_1 will equal 0. When the value of g_1 is significantly above 0, a distribution will be positively skewed,

and when it is significantly below 0, a distribution will be negatively skewed. Although the normal distribution is symmetrical (with $g_1 = 0$), as noted earlier, not all symmetrical distributions are normal. Examples of nonnormal distributions that are symmetrical are the t distribution and the binomial distribution, when $\pi_1 = .5$ (the meaning of the notation $\pi_1 = .5$ is explained in Section I of the **binomial sign test for a single sample (Test 9)**).

It was also noted in the **Introduction** that some sources (e.g., D'Agostino (1970, 1986) and D'Agostino *et al.* (1990)) convert the value of g_1 into the statistic $\sqrt{b_1}$. The latter is an estimate of a population parameter designated $\sqrt{\beta_1}$ (where β represents the lower case Greek letter **beta**), which is also employed to represent skewness. When a distribution is symmetrical (such as in the case of a normal distribution), the value of $\sqrt{b_1}$ will equal 0. When the value of $\sqrt{b_1}$ is significantly above 0, a distribution will be positively skewed, and when it is significantly below 0, a distribution will be negatively skewed.

The **single-sample test for evaluating population skewness** is the procedure for determining whether a g_1 and/or $\sqrt{b_1}$ value deviate significantly from 0. The normal distribution is employed to provide an approximation of the exact sampling distribution for the statistics g_1 and $\sqrt{b_1}$. Thus, the test statistic computed for the **single-sample test for evaluating population skewness** is a z value.

II. Example

Example 4.1 *A researcher wishes to evaluate the data in three samples (comprised of 10 scores per sample) for skewness. Specifically, the researcher wants to determine whether or not the samples meet the criteria for symmetry as opposed to positive versus negative skewness. The three samples will be designated **Sample A**, **Sample B**, and **Sample C**. The researcher has reason to believe that **Sample A** is derived from a symmetrical population distribution, **Sample B** from a negatively skewed population distribution, and **Sample C** from a positively skewed population distribution. The data for the three distributions are presented below.*

Distribution A: 0, 0, 0, 5, 5, 5, 5, 10, 10, 10

Distribution B: 0, 1, 1, 9, 9, 10, 10, 10, 10, 10

Distribution C: 0, 0, 0, 0, 0, 1, 1, 9, 9, 10

Are the data consistent with what the researcher believes to be true regarding the underlying population distributions?

III. Null versus Alternative Hypotheses

Null hypothesis $H_0: \gamma_1 = 0$ or $H_0: \sqrt{\beta_1} = 0$

(The underlying population distribution the sample represents is **symmetrical** — in which case the population parameters γ_1 and $\sqrt{\beta_1}$ are equal to 0.)

Alternative hypothesis $H_1: \gamma_1 \neq 0$ or $H_1: \sqrt{\beta_1} \neq 0$

(The underlying population distribution the sample represents is **not symmetrical** — in which case the population parameters γ_1 and $\sqrt{\beta_1}$ are not equal to 0. This is a **nondirectional alternative hypothesis**, and it is evaluated with a **two-tailed test**. In order to be supported, the absolute value of z must be equal to or greater than the tabled critical two-tailed z value at the prespecified level of significance. Thus, either a significant positive z value or a significant negative z value will provide support for this alternative hypothesis.)

or

$$H_1: \gamma_1 > 0 \text{ or } H_1: \sqrt{\beta_1} > 0$$

(The underlying population distribution the sample represents is **positively skewed** — in which case the population parameters γ_1 and $\sqrt{\beta_1}$ are greater than 0. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. It will only be supported if the sign of z is positive, and the absolute value of z is equal to or greater than the tabled critical one-tailed z value at the prespecified level of significance.)

or

$$H_1: \gamma_1 < 0 \text{ or } H_1: \sqrt{\beta_1} < 0$$

(The underlying population distribution the sample represents is **negatively skewed** — in which case the population parameters γ_1 and $\sqrt{\beta_1}$ are less than 0. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. It will only be supported if the sign of z is negative, and the absolute value of z is equal to or greater than the tabled critical one-tailed z value at the prespecified level of significance.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis is rejected.

IV. Test Computations

The three distributions presented in Example 4.1 are identical to **Distributions A, B, and C** employed in the **Introduction** to demonstrate the computation of the values m_3 , g_1 , and $\sqrt{b_1}$. Employing Equations I.17/I.18, I.19, and I.20, the following values were previously computed for m_3 , g_1 , and $\sqrt{b_1}$ for **Distributions A, B, and C**: $m_{3_A} = 0$, $m_{3_B} = -86.67$, $m_{3_C} = 86.67$, $g_{1_A} = 0$, $g_{1_B} = -1.02$, $g_{1_C} = 1.02$, and $\sqrt{b_{1_A}} = 0$, $\sqrt{b_{1_B}} = -.86$, $\sqrt{b_{1_C}} = .86$ (the computation of the latter values is summarized in [Tables I.2–I.4](#)).

Equations 4.2–4.8 (which are presented in Zar (1999, pp. 115–116)) summarize the steps that are involved in computing the test statistic (which, as is noted above, is a z value) for the **single-sample test for evaluating population skewness**. Zar (1999) states that Equation 4.8 provides a good approximation of the exact probabilities for the sampling distribution of g_1 (which is employed to compute the value of $\sqrt{b_1}$ that is used in Equation 4.2), when $n \geq 9$. Note that in Equations 4.6 and 4.8, the notation \ln represents the natural logarithm of a number (which is defined in Endnote 5 in the **Introduction**).

$$A = \sqrt{b_1} \sqrt{\frac{(n+1)(n+3)}{6(n-2)}} \quad \text{(Equation 4.2)}$$

$$B = \frac{3(n^2 + 27n - 70)(n+1)(n+3)}{(n-2)(n+5)(n+7)(n+9)} \quad \text{(Equation 4.3)}$$

$$C = \sqrt{2(B-1)} - 1 \quad \text{(Equation 4.4)}$$

$$D = \sqrt{C} \quad \text{(Equation 4.5)}$$

$$E = \frac{1}{\sqrt{\ln D}} \quad \text{(Equation 4.6)}$$

$$F = \frac{A}{\sqrt{\frac{2}{C-1}}} \quad \text{(Equation 4.7)}$$

$$z = E \ln(F + \sqrt{F^2 + 1}) \quad \text{(Equation 4.8)}$$

Employing Equations 4.2–4.8, the values $z_A = 0$, $z_B = -1.53$, and $z_C = 1.53$ are computed for **Distributions A, B, and C**.

Distribution A

$$A = 0 \sqrt{\frac{(10+1)(10+3)}{6(10-2)}} = 0$$

$$B = \frac{3[(10)^2 + 27(10) - 70](10+1)(10+3)}{(10-2)(10+5)(10+7)(10+9)} = 3.32$$

$$C = \sqrt{2(3.32-1)} - 1 = 1.15$$

$$D = \sqrt{1.15} = 1.07$$

$$E = \frac{1}{\sqrt{\ln 1.07}} = 3.84$$

$$F = \frac{0}{\sqrt{\frac{2}{1.15-1}}} = 0$$

$$z_A = 3.84 \ln[0 + \sqrt{(0)^2 + 1}] = 0$$

Distribution B

$$A = -.86 \sqrt{\frac{(10+1)(10+3)}{6(10-2)}} = -1.48$$

$$B = \frac{3[(10)^2 + 27(10) - 70](10+1)(10+3)}{(10-2)(10+5)(10+7)(10+9)} = 3.32$$

$$C = \sqrt{2(3.32-1)} - 1 = 1.15$$

$$D = \sqrt{1.15} = 1.07$$

$$E = \frac{1}{\sqrt{\ln 1.07}} = 3.84$$

$$F = \frac{-1.48}{\sqrt{\frac{2}{1.15 - 1}}} = -.41$$

$$z_B = 3.84 \ln[-.41 + \sqrt{(-.41)^2 + 1}] = -1.53$$

Distribution C

$$A = .86 \sqrt{\frac{(10 + 1)(10 + 3)}{6(10 - 2)}} = 1.48$$

$$B = \frac{3[(10)^2 + 27(10) - 70](10 + 1)(10 + 3)}{(10 - 2)(10 + 5)(10 + 7)(10 + 9)} = 3.32$$

$$C = \sqrt{2(3.32 - 1)} - 1 = 1.15$$

$$D = \sqrt{1.15} = 1.07$$

$$E = \frac{1}{\sqrt{\ln 1.07}} = 3.84$$

$$F = \frac{1.48}{\sqrt{\frac{2}{1.15 - 1}}} = .41$$

$$z_C = 3.84 \ln[.41 + \sqrt{(.41)^2 + 1}] = 1.53$$

V. Interpretation of the Test Results

The obtained values $z_A = 0$, $z_B = -1.53$, and $z_C = 1.53$ are evaluated with **Table A1 (Table of the Normal Distribution)** in the **Appendix**. In **Table A1** the tabled critical two-tailed .05 and .01 values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed .05 and .01 values are $z_{.05} = 1.65$ and $z_{.01} = 2.33$. Since the computed **absolute values** $z_A = 0$, $z_B = 1.53$, and $z_C = 1.53$ are all less than the tabled critical two-tailed value $z_{.05} = 1.96$ and the tabled critical one-tailed value $z_{.05} = 1.65$, the null hypothesis cannot be rejected, regardless of which alternative hypothesis is employed.

The computation of the value $z_A = 0$ for **Distribution A** is consistent with the fact that the latter distribution is employed to represent a symmetrical distribution. Thus, the nondirectional alternative hypothesis $H_1: \gamma_1 \neq 0$ (or $H_1: \sqrt{\beta_1} \neq 0$) is not supported. Whenever a distribution has perfect symmetry g_1 (as well as $\sqrt{b_1}$), will equal 0, and consequently the value computed for z will also equal 0.

Although not statistically significant, the data for **Distribution B** are consistent with the directional alternative hypothesis $H_1: \gamma_1 < 0$ (or $H_1: \sqrt{\beta_1} < 0$). Similarly, although not statistically significant, the data for **Distribution C** are consistent with the directional alternative

hypothesis $H_1: \gamma_1 > 0$ (or $H_1: \sqrt{\beta_1} > 0$). Note that because $g_{1_B} = -1.02$ and $\sqrt{b_{1_B}} = -.86$ are negative numbers, a negative z value is obtained for **Distribution B** (which is hypothesized to represent a negatively skewed distribution). In the same respect, since $g_{1_C} = 1.02$ and $\sqrt{b_{1_C}} = .86$ are positive numbers, a positive z value is obtained for **Distribution C** (which is hypothesized to represent a positively skewed distribution). Whenever a distribution is negatively skewed, the computed value of z will be a negative number, and whenever a distribution is positively skewed, the computed value of z will be a positive number. The fact that the values $z_B = -1.53$ and $z_C = 1.53$ are not statistically significant (although they are not that far removed from the tabled critical one-tailed .05 value $z_{.05} = 1.65$), in large part may be attributed to the fact that a small sample size (i.e., $n = 10$) is employed to represent each distribution. A small sample size severely reduces the power of a statistical test, making it more difficult to obtain a statistically significant result (i.e., in this case, a significant deviation from symmetry).

It should be noted that in most instances when a researcher has reason to evaluate a distribution with regard to skewness, he will employ a sample size which is much larger than the value $n = 10$ employed in Example 4.1. Section VII discusses tables that document the exact sampling distribution for the g_1 statistic, and contrasts the results obtained with the latter tables with the results obtained in this section.

VI. Additional Analytical Procedures for the Single-Sample Test for Evaluating Population Skewness

1. Note on the D'Agostino–Pearson test of normality (Test 5a) Most researchers would not consider the result of the **single-sample test for evaluating population skewness**, in and of itself, as sufficient evidence for establishing goodness-of-fit for normality. As noted in Section I, a procedure is presented in Section VI of the **single-sample test for evaluating population kurtosis**, which employs the z value based on the computed value of g_1 (which is employed to compute the value of $\sqrt{b_1}$ that is used in Equation 4.2) and a z value based on computed value of g_2 (which is a measure of kurtosis that is discussed in the **Introduction** and in the **single-sample test for evaluating population kurtosis**) to evaluate whether or not a set of data is derived from a normal distribution. The latter procedure is referred to as the **D'Agostino–Pearson test of normality**.

VII. Additional Discussion of the Single-Sample Test for Evaluating Population Skewness

1. Exact tables for the single-sample test for evaluating population skewness Zar (1999) has derived exact tables for the absolute value of the g_1 statistic for sample sizes in the range $9 \leq n \leq 1000$. By employing the exact tables, one can avoid the tedious computations that are described in Section IV for the **single-sample test for evaluating population skewness** (which employs the normal distribution to approximate the exact sampling distribution). In Zar's (1999) tables, the tabled critical two-tailed .05 and .01 values for g_1 are $g_{1.05} = 1.359$ and $g_{1.01} = 1.846$, and the tabled critical one-tailed .05 and .01 values are $g_{1.05} = 1.125$ and $g_{1.01} = 1.643$. In order to reject the null hypothesis, the computed absolute value of g_1 must be equal to or greater than the tabled critical value (and if a directional alternative hypothesis is evaluated, the sign of g_1 must be in the predicted direction). The probabilities derived for Example 4.1 (through use of Equation 4.8) are extremely close to the exact probabilities listed in Zar (1999). The probability for **Distribution A** is identical to Zar's (1999) exact probability. With respect to **Distributions B** and **C**, the probabilities listed in Zar's (1999) tables for the values $g_{1_B} = -1.02$ and

$g_{1c} = 1.02$ are very close to the tabled probabilities in [Table A1](#) for the computed values $z_B = -1.53$ and $z_C = 1.53$. Note that the absolute value $g_1 = 1.02$ just falls short of being significant at the .05 level if a one-tailed analysis is conducted. In the case of Example 4.1, the same conclusions regarding the null hypothesis will be reached, regardless of whether or not one employs the normal approximation or Zar's (1999) tables.

2. Note on a nonparametric test for evaluating skewness Zar (1999, pp. 119–120) describes a **nonparametric procedure** for evaluating skewness/symmetry around the median of a distribution (as opposed to the mean). The latter test is based on the **Wilcoxon signed-ranks test (Test 6)**, which is one of the nonparametric procedures described in this book.

VIII. Additional Examples Illustrating the Use of the Single-Sample Test for Evaluating Population Skewness

No additional examples will be presented in this section.

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Test 5

The Single-Sample Test for Evaluating Population Kurtosis

(Parametric Test Employed with Interval/Ratio Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test Does a sample of n subjects (or objects) come from a population distribution that is mesokurtic?

Relevant background information on test Prior to reading this section the reader should review the discussion of **kurtosis** in the **Introduction**. As noted in the **Introduction**, kurtosis is a measure reflecting the degree of peakedness of a distribution. From a statistical perspective, the kurtosis of a distribution represents the **fourth moment about the mean** (m_4), which is represented by Equation 5.1 (which is identical to Equation I.15).

$$m_4 = \frac{\sum(X - \bar{X})^4}{n} \quad (\text{Equation 5.1})$$

Kurtosis can be employed as a criterion for determining the **goodness-of-fit** of data with respect to a normal distribution. Various sources (e.g., Anscombe and Glynn (1983), D'Agostino (1986), D'Agostino and Stephens (1986), and D'Agostino *et al.* (1990)) state that in spite of the fact that it is not as commonly employed as certain alternative goodness-of-fit tests, the **single-sample test for evaluating population kurtosis** provides an excellent test for evaluating a hypothesis of goodness-of-fit for normality, when it is employed in conjunction with the result of the **single-sample test for evaluating population skewness (Test 4)**. The results of the latter two tests are employed in the **D'Agostino–Pearson test of normality (Test 5a)**, which is described in Section VI. D'Agostino (1986), D'Agostino *et al.* (1990), and Zar (1999) state that the **D'Agostino–Pearson test of normality** provides for a more powerful test of the normality hypothesis than does either the **Kolmogorov–Smirnov goodness-of-fit test for a single sample (Test 7)** or the **chi-square goodness-of-fit test (Test 8)** (both of which are described later in the book). D'Agostino *et al.* (1990) state that because of their lack of power, the latter two tests should not be employed for assessing normality. Other sources, however, take a more favorable attitude towards the **Kolmogorov–Smirnov goodness-of-fit test for a single sample** and the **chi-square goodness-of-fit test** as tests of goodness-of-fit for normality (e.g., Conover (1980, 1999), Daniel (1990), Hollander and Wolfe (1999), Marascuilo and McSweeney (1977), Siegel and Castellan (1988), and Sprent (1993)). It should be noted that the **single-sample test for evaluating population kurtosis** is a test of mesokurtic normality — in other words, whether or not a distribution is mesokurtic.

In the **Introduction** it was noted that since the value computed for m_4 is in units of the fourth power, it is often converted into the unitless statistic g_2 . The latter, which is an estimate of the population parameter γ_2 (where γ represents the lower case Greek letter **gamma**), is commonly employed to express kurtosis. When a distribution is mesokurtic, the value of g_2 will

equal 0. When the value of g_2 is significantly above 0, a distribution will be leptokurtic, and when it is significantly below 0, a distribution will be platykurtic.

It was also noted in the **Introduction** that some sources (e.g., Anscombe and Glynn (1983), D'Agostino (1986), and D'Agostino *et al.* (1990)) convert the value of g_2 into the statistic b_2 . The latter is an estimate of a population parameter designated β_2 (where β represents the lower case Greek letter **beta**), which is also employed to represent kurtosis. When a distribution is mesokurtic, the value of b_2 will equal $[3(n-1)]/(n+1)$. Inspection of the latter equation reveals that as the value of the sample size increases, the value of b_2 approaches 3. When the value computed for b_2 is significantly below $[3(n-1)]/(n+1)$, a distribution will be platykurtic. When the value the computed for b_2 is significantly greater than $[3(n-1)]/(n+1)$, a distribution will be leptokurtic.

The **single-sample test for evaluating population kurtosis** is the procedure for determining whether a g_2 and/or b_2 value deviate significantly from the expected value for a mesokurtic distribution. As noted earlier, any normal distribution will always be mesokurtic, with the following expected computed values: $g_2 = 0$ and $b_2 = 3$.

The normal distribution is employed to provide an approximation of the exact sampling distribution for the statistics g_2 and b_2 . Thus, the test statistic computed for the **single-sample test for evaluating population kurtosis** is a z value.

II. Example

Example 5.1 *A researcher wishes to evaluate the data in two samples (comprised of 20 scores per sample) for kurtosis. The two samples will be designated **Sample E** and **Sample F**. The researcher has reason to believe that **Sample E** is derived from a leptokurtic population distribution, while **Sample F** is derived from a platykurtic population distribution. The data for the two distributions are presented below.*

Distribution E: 2, 7, 8, 8, 8, 9, 9, 9, 10, 10, 10, 10, 11, 11, 11, 12, 12, 12, 13, 18

Distribution F: 0, 1, 3, 3, 5, 5, 8, 8, 10, 10, 10, 10, 12, 12, 15, 15, 17, 17, 19, 20

Are the data consistent with what the researcher believes to be true regarding the underlying population distributions?

III. Null versus Alternative Hypotheses

Null hypothesis

$$H_0: \gamma_2 = 0 \text{ or } H_0: \beta_2 = 3$$

(The underlying population distribution the sample represents is **mesokurtic**—in which case the population parameter γ_2 is equal to 0, and the population parameter β_2 is equal to 3.)

Alternative hypothesis

$$H_1: \gamma_2 \neq 0 \text{ or } H_1: \beta_2 \neq 3$$

(The underlying population distribution the sample represents is **not mesokurtic**—in which case the population parameter γ_2 is not equal to 0, and the population parameter β_2 is not equal to 3. This is a **nondirectional alternative hypothesis**, and it is evaluated with a **two-tailed test**. In order to be supported, the absolute value of z must be equal to or greater than the tabled critical two-tailed z value at the prespecified level of significance.)

or

$$H_1: \gamma_2 > 0 \text{ or } H_1: \beta_2 > 3$$

(The underlying population distribution the sample represents is **leptokurtic** — in which case the population parameter γ_2 is greater than 0, and the population parameter β_2 is greater than 3. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. It will only be supported if $g_2 > 0$, and the absolute value of z is equal to or greater than the tabled critical one-tailed z value at the prespecified level of significance.)

or

$$H_1: \gamma_2 < 0 \text{ or } H_1: \beta_2 < 3$$

(The underlying population distribution the sample represents is **platykurtic** — in which case the population parameter γ_2 is less than 0, and the population parameter β_2 is less than 3. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. It will only be supported if $g_2 < 0$, and the absolute value of z is equal to or greater than the tabled critical one-tailed z value at the prespecified level of significance.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis is rejected.

IV. Test Computations

The two distributions presented in Example 5.1 are identical to **Distributions E** and **F** employed in the **Introduction** to demonstrate the computation of the values m_4 , g_2 , and b_2 . Employing Equations I.21/I.22, I.23 and I.24, the following values were previously computed for m_4 , g_2 , and b_2 for **Distributions E** and **F**: $m_{4_E} = 307.170$, $m_{4_F} = -1181.963$, $g_{2_E} = 3.596$, $g_{2_F} = -.939$, and $b_{2_E} = 5.472$, $b_{2_F} = 1.994$ (the computation of the latter values is summarized in [Tables I.5–I.6](#)).

Equations 5.2–5.7 (which are presented in Zar (1999, pp. 116–118) summarize the steps that are involved in computing the test statistic (which, as is noted above, is a z value) for the **single-sample test for evaluating population kurtosis**. Zar (1999) states that Equation 5.7 provides a good approximation of the exact probabilities for the sampling distribution of g_2 , when $n \geq 20$.

$$G = \frac{24n(n-2)(n-3)}{(n+1)^2(n+3)(n+5)} \quad (\text{Equation 5.2})$$

$$H = \frac{(n-2)(n-3)|g_2|}{(n+1)(n-1)\sqrt{G}} \quad (\text{Equation 5.3})$$

$$J = \frac{6(n^2 - 5n + 2)}{(n+7)(n+9)} \sqrt{\frac{6(n+3)(n+5)}{n(n-2)(n-3)}} \quad (\text{Equation 5.4})$$

$$K = 6 + \frac{8}{J} \left[\frac{2}{J} + \sqrt{1 + \frac{4}{J^2}} \right] \quad (\text{Equation 5.5})$$

$$L = \frac{1 - \frac{2}{K}}{1 + H \sqrt{\frac{2}{K-4}}} \quad (\text{Equation 5.6})$$

$$z = \frac{1 - \frac{2}{9K} - \sqrt[3]{L}}{\sqrt{\frac{2}{9K}}} \quad \text{(Equation 5.7)}$$

Employing Equations 5.2–5.7, the values $z_E = 2.40$, and $z_F = 1.07$ are computed for **Distributions E and F**.

Distribution E

$$G = \frac{(24)(20)(20 - 2)(20 - 3)}{(20 + 1)^2(20 + 3)(20 + 5)} = .579$$

$$H = \frac{(20 - 2)(20 - 3)|3.596|}{(20 + 1)(20 - 1)\sqrt{.579}} = 3.624$$

$$J = \frac{6[(20)^2 - 5(20) + 2]}{(20 + 7)(20 + 9)} \sqrt{\frac{6(20 + 3)(20 + 5)}{20(20 - 2)(20 - 3)}} = 1.737$$

$$K = 6 + \frac{8}{1.737} \left[\frac{2}{1.737} + \sqrt{1 + \frac{4}{(1.737)^2}} \right] = 18.325$$

$$L = \frac{1 - \frac{2}{18.325}}{1 + (3.624) \sqrt{\frac{2}{18.325 - 4}}} = .379$$

$$z_E = \frac{1 - \frac{2}{(9)(18.325)} - \sqrt[3]{.379}}{\sqrt{\frac{2}{(9)(18.325)}}} = 2.40$$

Distribution F

$$G = \frac{(24)(20)(20 - 2)(20 - 3)}{(20 + 1)^2(20 + 3)(20 + 5)} = .579$$

$$H = \frac{(20 - 2)(20 - 3)|-.939|}{(20 + 1)(20 - 1)\sqrt{.579}} = .946$$

$$J = \frac{6[(20)^2 - 5(20) + 2]}{(20 + 7)(20 + 9)} \sqrt{\frac{6(20 + 3)(20 + 5)}{20(20 - 2)(20 - 3)}} = 1.737$$

$$K = 6 + \frac{8}{1.737} \left[\frac{2}{1.737} + \sqrt{1 + \frac{4}{(1.737)^2}} \right] = 18.325$$

$$L = \frac{1 - \frac{2}{18.325}}{1 + (.946)\sqrt{\frac{2}{18.325 - 4}}} = .659$$

$$z_F = \frac{1 - \frac{2}{(9)(18.325)} - \sqrt[3]{.659}}{\sqrt{\frac{2}{(9)(18.325)}}} = 1.07$$

V. Interpretation of the Test Results

The obtained values $z_E = 2.40$ and $z_F = 1.07$ are evaluated with **Table A1 (Table of the Normal Distribution)** in the **Appendix**. In **Table A1** the tabled critical two-tailed .05 and .01 values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed .05 and .01 values are $z_{.05} = 1.65$ and $z_{.01} = 2.33$.

With respect to **Distribution E**, since the obtained value $z_E = 2.40$ is greater than the tabled critical two-tailed value $z_{.05} = 1.96$, the nondirectional alternative hypothesis $H_1: \gamma_2 \neq 0$ (or $H_1: \beta_2 \neq 3$) is supported at the .05 level. However, it is not supported at the .01 level, since $z_E = 2.40$ is less than the tabled critical two-tailed value $z_{.01} = 2.58$. The directional alternative hypothesis $H_1: \gamma_2 > 0$ (or $H_1: \beta_2 > 3$) is supported at both the .05 and .01 levels, since the obtained value $g_{2_E} = 3.596$ is a positive number, and the obtained value $z_E = 2.40$ is greater than the tabled critical one-tailed values $z_{.05} = 1.65$ and $z_{.01} = 2.33$.

The directional alternative hypothesis $H_1: \gamma_2 < 0$ (or $H_1: \beta_2 < 3$) not supported, since in order for the latter alternative hypothesis to be supported, the computed value of g_2 must be a negative number.

With respect to **Distribution E**, the result of the **single-sample test for evaluating population kurtosis** allows one to conclude that there is a high likelihood the sample is derived from a population which is leptokurtic.

In the case of **Distribution F**, since the obtained value $z_F = 1.07$ is less than the tabled critical two-tailed value $z_{.05} = 1.96$ and the tabled critical one-tailed value $z_{.05} = 1.65$, the null hypothesis cannot be rejected, regardless of which alternative hypothesis is employed. Although the value $g_{2_F} = -.939$ computed for **Distribution F** is a negative number, its absolute value is not large enough to warrant the conclusion that the sample is derived from a population that is platykurtic.

It should be noted that in most instances when a researcher has reason to evaluate a distribution with regard to kurtosis, he will employ a sample size which is much larger than the value $n = 20$ employed in Example 5.1. Section VII discusses tables that document the exact sampling distribution for the g_2 statistic, and contrasts the results obtained with the latter tables with the results obtained in this section.

VI. Additional Analytical Procedures for the Single-Sample Test for Evaluating Population Kurtosis

1. Test 5a: The D'Agostino–Pearson test of normality Many researchers would not consider the result of the **single-sample test for evaluating population kurtosis**, in and of itself, as sufficient evidence for establishing goodness-of-fit for normality. In this section a procedure (to

be referred to as the **D'Agostino–Pearson test of normality**) will be described which employs the computed value of g_2 and the computed value of g_1 (which is a measure of skewness discussed in the **Introduction** and in the **single-sample test for evaluating population skewness**) to evaluate whether a set of data is derived from a normal distribution.

The **D'Agostino–Pearson test of normality** was developed by D'Agostino and Pearson (1973), who state that the test is the most effective procedure for assessing goodness-of-fit for a normal distribution. D'Agostino (1973, 1986) and Zar (1999) claim that the **D'Agostino–Pearson test of normality** is more effective for assessing goodness-of-fit than the more commonly employed **Kolmogorov–Smirnov goodness-of-fit test for a single sample** and the **chi-square goodness-of-fit test**.

The null and alternative hypotheses that are evaluated with the **D'Agostino–Pearson test of normality** are as follows.

Null hypothesis H_0 : The sample is derived from a normally distributed population.

Alternative hypothesis H_1 : The sample is not derived from a normally distributed population. This is a **nondirectional alternative hypothesis**.

The test statistic for the **D'Agostino–Pearson test of normality** is computed with Equation 5.8.

$$\chi^2 = z_{g_1}^2 + z_{g_2}^2 \quad (\text{Equation 5.8})$$

The values $z_{g_1}^2$ and $z_{g_2}^2$ are respectively the square of the z values computed with Equation 4.8 and Equation 5.7. Equation 4.8 is employed to compute the test statistic z_{g_1} (which is based on the value computed for $\sqrt{b_1}$) for the **single-sample test for evaluating population skewness**, and Equation 5.7 is employed to compute the test statistic z_{g_2} for the **single-sample test for evaluating population kurtosis**. The computed value of χ^2 is evaluated with **Table A4 (Table of the Chi-Square Distribution)** in the **Appendix**. The degrees of freedom employed in the analysis will always be $df = 2$. The tabled critical .05 and .01 chi-squared values in **Table A4** for $df = 2$ are $\chi_{.05}^2 = 5.99$ and $\chi_{.01}^2 = 9.21$.¹ If the computed value of chi-square is equal to or greater than either of the aforementioned values, the null hypothesis can be rejected at the appropriate level of significance. If the null hypothesis is rejected, a researcher can conclude that a set of data does not fit a normal distribution. Through examination of the results of the **single-sample test for evaluating population skewness** and the **single-sample test for evaluating population kurtosis**, the researcher can determine if rejection of the null hypothesis is the result of a lack of symmetry and/or a departure from mesokurtosis.

It happens to be the case that **Distribution F** is a symmetrical distribution, and thus $g_{1_F} = 0$ and $\sqrt{b_{1_F}} = 0$. Consequently, the value computed with Equation 4.7 will be $z_{g_1} = 0$. When the latter value, along with the value $z_{g_2} = 1.07$ computed for **Distribution F** with Equation 5.7, is substituted in Equation 5.8, the value $\chi^2 = 1.14$ is obtained.

$$\chi^2 = (0)^2 + (1.07)^2 = 1.14$$

Since the value $\chi^2 = 1.14$ is less than the tabled critical value $\chi_{.05}^2 = 5.99$, we are not able to reject the null hypothesis. Thus, we cannot conclude that the population distribution for **Distribution F** is nonnormal.

It happens to be the case that **Distribution E** is also a symmetrical distribution, and thus

$g_{1_E} = 0$ and $\sqrt{b_{1_E}} = 0$. Consequently, the value computed with Equation 4.7 will be $z_{g_1} = 0$. When the latter value, along with the value $z_{g_2} = 2.40$ computed for **Distribution E** with Equation 5.7, is substituted in Equation 5.8, the value $\chi^2 = 5.76$ is obtained (the latter value resulting entirely from the square of the significant value $z_{g_2} = 2.40$, which indicated that **Distribution E** is leptokurtic).

$$\chi^2 = (0)^2 + (2.40)^2 = 5.76$$

Since the value $\chi^2 = 5.76$ is less (although not by much) than the tabled critical value $\chi^2_{.05} = 5.99$, we are not able to reject the null hypothesis. However, the analysis of the data in Section IV with the **single-sample test for evaluating population kurtosis** suggests that **Distribution E** is clearly leptokurtic, and that in itself might be sufficient grounds for some researchers to conclude that it is unlikely that the underlying population is normal. Thus, in spite of the nonsignificant result with the **D'Agostino–Pearson test of normality**, some researchers might view it prudent to reject the null hypothesis purely on the basis of the outcome of the **single-sample test for evaluating population kurtosis**.

VII. Additional Discussion of the Single-Sample Test for Evaluating Population Kurtosis

1. Exact tables for the single-sample test for evaluating population kurtosis Zar (1999) has derived exact tables for the absolute value of the g_2 statistic for sample sizes in the range $20 \leq n \leq 1000$. By employing the exact tables, one can avoid the tedious computations that are described in Section IV for the **single-sample test for evaluating population kurtosis** (which employs the normal distribution to approximate the exact sampling distribution). In Zar's (1999) tables, the tabled critical two-tailed .05 and .01 values for g_2 are $g_{2_{.05}} = 2.486$ and $g_{2_{.01}} = 4.121$, and the tabled critical one-tailed .05 and .01 values are $g_{2_{.05}} = 1.850$ and $g_{2_{.01}} = 3.385$. In order to reject the null hypothesis, the computed absolute value of g_2 must be equal to or greater than the tabled critical value (and if a directional alternative hypothesis is evaluated, the sign of g_2 must be in the predicted direction). The probabilities derived for Example 5.1 (through use of Equation 5.7) are very close to the exact probabilities listed in Zar (1999). In other words, the probabilities listed in Zar's (1999) tables for the absolute values $g_{2_E} = 3.596$ and $g_{2_F} = .939$ are almost the same as the tabled probabilities in **Table A1** for the computed values $z_E = 2.40$ and $z_F = 1.07$. In the case of Example 5.1, the same conclusions regarding the null hypothesis will be reached, regardless of whether one employs the normal approximation or Zar's (1999) tables.

VIII. Additional Examples Illustrating the Use of the Single-Sample Test for Evaluating Population Kurtosis

No additional examples will be presented in this section.

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Endnotes

1. When **Table A4** is employed to evaluate a chi-square value computed for the **D’Agostino–Pearson test of normality**, the following protocol is employed. The tabled critical values for $df = 2$ are derived from the right tail of the distribution. Thus, the tabled critical .05 chi-square value (to be designated $\chi^2_{.05}$) will be the tabled chi-square value at the 95th percentile. In the same respect, the tabled critical .01 chi-square value (to be designated $\chi^2_{.01}$) will be the tabled chi-square value at the 99th percentile. For further clarification of interpretation of the critical values in **Table A4**, the reader should consult Section V of the **single-sample chi-square test for a population variance (Test 3)**.

Test 6

The Wilcoxon Signed-Ranks Test (Nonparametric Test Employed with Ordinal Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test Does a sample of n subjects (or objects) come from a population in which the median value (θ) equals a specified value?

Relevant background information on test The **Wilcoxon signed-ranks test** (Wilcoxon (1945, 1949)) is a nonparametric procedure employed in a hypothesis testing situation involving a single sample in order to determine whether a sample is derived from a population with a median of θ . (The population median will be represented by the notation θ , which is the lower case Greek letter **theta**.) If the **Wilcoxon signed-ranks test** yields a significant result, the researcher can conclude there is a high likelihood the sample is derived from a population with a median value other than θ .

The **Wilcoxon signed-ranks test** is based on the following assumptions:¹ a) The sample has been randomly selected from the population it represents; b) The original scores obtained for each of the subjects/objects are in the format of interval/ratio data; and c) The underlying population distribution is symmetrical. When there is reason to believe that the latter assumption is violated, Daniel (1990), among others, recommends that the **binomial sign test for a single sample (Test 9)** be employed in place of the **Wilcoxon signed-ranks test**.² Proponents of nonparametric tests recommend that the **Wilcoxon signed-ranks test** be employed in place of the **single-sample t test (Test 2)** when there is reason to believe that the normality assumption of the latter test has been saliently violated.³ It should be noted that all of the other tests in this text that rank data (with the exception of the **Wilcoxon matched-pairs signed-ranks test (Test 18)** and the **Moses test for equal variability (Test 15)**) rank the original interval/ratio scores of subjects. The **Wilcoxon signed-ranks test**, however, does not rank subjects' original interval/ratio scores, but instead ranks difference scores — specifically, the obtained difference between each subject's score and the hypothesized value of the population median. For this reason, some sources categorize the **Wilcoxon signed-ranks test** as a test of interval/ratio data. Most sources, however, (including this book) categorize the test as one involving ordinal data, because a ranking procedure is part of the test protocol.

II. Example

Example 6.1 *A physician states that the median number of times he sees each of his patients during the year is five. In order to evaluate the validity of this statement, he randomly selects ten of his patients and determines the number of office visits each of them made during the past year. He obtains the following values for the ten patients in his sample: 9, 10, 8, 4, 8, 3, 0, 10, 15, 9. Do the data support his contention that the median number of times he sees a patient is five?*

III. Null versus Alternative Hypotheses

Null hypothesis

$$H_0: \theta = 5$$

(The median of the population the sample represents equals 5. With respect to the sample data, this translates into the sum of the ranks of the positive difference scores being equal to the sum of the ranks of the negative difference scores (i.e., $\sum R_+ = \sum R_-$.)

Alternative hypothesis

$$H_1: \theta \neq 5$$

(The median of the population the sample represents does not equal 5. With respect to the sample data, this translates into the sum of the ranks of the positive difference scores not being equal to the sum of the ranks of the negative difference scores (i.e., $\sum R_+ \neq \sum R_-$). This is a **non-directional alternative hypothesis** and it is evaluated with a **two-tailed test**.)

or

$$H_1: \theta > 5$$

(The median of the population the sample represents is some value greater than 5. With respect to the sample data, this translates into the sum of the ranks of the positive difference scores being greater than the sum of the ranks of the negative difference scores (i.e., $\sum R_+ > \sum R_-$). This is a **directional alternative hypothesis** and it is evaluated with a **one-tailed test**.)

or

$$H_1: \theta < 5$$

(The median of the population the sample represents is some value less than 5. With respect to the sample data, this translates into the sum of the ranks of the positive difference scores being less than the sum of the ranks of the negative difference scores (i.e., $\sum R_+ < \sum R_-$). This is a **directional alternative hypothesis** and it is evaluated with a **one-tailed test**.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis is rejected.

IV. Test Computations

The data for Example 6.1 are summarized in [Table 6.1](#).

The scores of the 10 subjects are recorded in Column 2 of [Table 6.1](#). In Column 3, a D score is computed for each subject. This score, which is referred to as a **difference score**, is the difference between a subject's score and the hypothesized value of the population median, $\theta = 5$. Column 4 contains the ranks of the difference scores. In ranking the difference scores for the **Wilcoxon signed-ranks test**, the following guidelines are employed:

a) The **absolute values** of the difference scores ($|D|$) are ranked (i.e., the sign of a difference score is not taken into account).

b) Any difference score that equals zero is not ranked. This translates into eliminating from the analysis any subject who yields a difference score of zero.

c) In ranking the absolute values of the difference scores, the following protocol should be employed: Assign a rank of 1 to the difference score with the lowest absolute value, a rank of 2 to the difference score with the second lowest absolute value, and so on until the highest rank is assigned to the difference score with the highest absolute value. When there are tied scores present, the average of the ranks involved is assigned to all difference scores tied for a given rank.

Table 6.1 Data for Example 6.1

Subject	X	$D = X - \theta$	Rank of $ D $	Signed rank of $ D $
1	9	4	5.5	5.5
2	10	5	8	8
3	8	3	3.5	3.5
4	4	-1	1	-1
5	8	3	3.5	3.5
6	3	-2	2	-2
7	0	-5	8	-8
8	10	5	8	8
9	15	10	10	10
10	9	4	5.5	5.5
				$\Sigma R^+ = 44$
				$\Sigma R^- = 11$

Because of this latter fact, when there are tied scores for either the lowest or highest difference scores, the rank assigned to the lowest difference score will be some value greater than 1, and the rank assigned to the highest difference score will be some value less than n . To further clarify how ties are handled, examine Table 6.2 which lists the **difference scores** of the 10 subjects. In the table, the difference scores (based on their absolute values) are arranged ordinarily, after which they are ranked employing the protocol described above.

Table 6.2 Ranking Procedure for Wilcoxon Signed-Ranks Test

Subject number	4	6	3	5	1	10	2	7	8	9
Subject's difference score	-1	-2	3	3	4	4	5	-5	5	10
Absolute value of difference score	1	2	3	3	4	4	5	5	5	10
Rank of $ D $	1	2	3.5	3.5	5.5	5.5	8	8	8	10

The difference score of Subject 4 has the lowest absolute value (i.e., 1), and because of this it is assigned a rank of 1. The next lowest absolute value for a difference score (2) is that of Subject 6, and thus it is assigned a rank of 2.⁴ The difference score of 3 (which is obtained for both Subjects 3 and 5) is the score that corresponds to the third rank-order. Since, however, there are two instance of this difference score, it will also use up the position reserved for the fourth rank-order (i.e., 3 and 4 are the two ranks that would be employed if, in fact, these two subjects did not have the identical difference score). Instead of arbitrarily assigning one of the subjects with a difference score of 3 a rank-order of 3 and the other subject a rank-order of 4, we compute the average of the two ranks that are involved (i.e., $(3 + 4)/2 = 3.5$), and assign that value as the rank-order for the difference scores of both subjects. The next rank-order in the sequence of the 10 rank-orders is 5. Once again, however, two subjects (Subjects 1 and 10) are tied for the difference score in the fifth ordinal position (which happens to involve a difference score of 4). Since, if not equal to one another, these two difference scores would involve the fifth and sixth ranks, we compute the average of these two ranks (i.e., $(5 + 6)/2 = 5.5$), and assign that value as the rank for the difference scores of Subjects 1 and 10. With respect to the next difference score (5), there is a three-way tie involving Subjects 2, 7, and 8 (keeping in mind that the absolute value of the difference score for Subject 7 is 5). The average of the three ranks which would be involved if the subjects had obtained different difference scores is computed (i.e., $(7 + 8 + 9)/3 = 8$), and that average value is assigned to the difference scores of Subjects 2, 7, and 8. Since the remaining

difference score of 10 (obtained by Subject 9) is the highest difference score, it is assigned the highest rank which equals 10.

It should be emphasized that in the **Wilcoxon signed-ranks test** it is essential that a rank of 1 be assigned to the difference score with the lowest absolute value, and that the highest rank be assigned to the difference score with the highest absolute value. In most other tests that involve ranking, the ranking procedure can be reversed (i.e., the same test statistic will be obtained if one assigns a rank of 1 to the highest score and the highest rank to the lowest score). However, if one reverses the ranking procedure in conducting the **Wilcoxon signed-ranks test**, it will invalidate the results of the test.

d) After ranking the absolute values of the difference scores, the sign of each difference score is placed in front of its rank. The signed ranks of the difference scores are listed in Column 5 of Table 6.1.

The sum of the ranks that have a positive sign (i.e., $\Sigma R+ = 44$) and the sum of the ranks that have a negative sign (i.e., $\Sigma R- = 11$) are recorded at the bottom of the Column 5 in Table 6.1. Equation 6.1 allows one to check the accuracy of these values. If the relationship indicated by Equation 6.1 is not obtained, it indicates an error has been made in the calculations. In Equation 6.1, n represents the number of signed ranks (i.e., the number of difference scores that are ranked).

$$\Sigma R+ + \Sigma R- = \frac{n(n + 1)}{2} \quad \text{(Equation 6.1)}$$

Employing the values $\Sigma R+ = 44$ and $\Sigma R- = 11$ in Equation 6.1, we confirm that the relationship described by the equation is true.

$$44 + 11 = \frac{(10)(11)}{2} = 55$$

It is important to note that in the event one or more subjects obtains a difference score of zero, such scores are not employed in the analysis. In such a case, the value of n in Equation 6.1 will only represent the number of scores that have been assigned ranks. Example 6.2 in Section VIII illustrates the use of the **Wilcoxon signed-ranks test** with data in which difference scores of zero are present.

V. Interpretation of the Test Results

As noted in Section III, if the sample is derived from a population with a median value equal to the hypothesized value of the population median (i.e., the null hypothesis is true), the values of $\Sigma R+$ and $\Sigma R-$ will be equal to one another. When $\Sigma R+$ and $\Sigma R-$ are equivalent, both of these values will equal $[n(n + 1)]/4$, which in the case of Example 6.1 will be $[(10)(11)]/4 = 27.5$. This latter value is commonly referred to as the **expected value** of the **Wilcoxon T statistic**.

If the value of $\Sigma R+$ is significantly greater than the value of $\Sigma R-$, it indicates there is a high likelihood the sample is derived from a population with a median value which is larger than the hypothesized value of the population median. On the other hand, if $\Sigma R-$ is significantly greater than $\Sigma R+$, it indicates there is a high likelihood the sample is derived from a population with a median value that is less than the hypothesized value of the population median. The fact that $\Sigma R+ = 44$ is greater than $\Sigma R- = 11$ indicates that the data are consistent with the directional alternative hypothesis $H_1: \theta > 5$. The question is, however, whether the difference is significant — i.e., whether it large enough to conclude that it is unlikely to be the result of chance.

The absolute value of the **smaller** of the two values $\Sigma R+$ versus $\Sigma R-$ is designated as the

Wilcoxon T test statistic. Since $\Sigma R^- = 11$ is smaller than $\Sigma R^+ = 44$, $T = 11$. The T value is interpreted by employing **Table A5 (Table of Critical T Values for Wilcoxon's Signed-Ranks and Matched-Pairs Signed-Ranks Tests)** in the **Appendix**. **Table A5** lists the critical two-tailed and one-tailed .05 and .01 T values in relation to the number of signed ranks in a set of data. In order to be significant, the obtained value of T must be **equal to or less than** the tabled critical T value at the prespecified level of significance.⁵ **Table 6.3** summarizes the tabled critical two-tailed and one-tailed .05 and .01 Wilcoxon T values for $n = 10$ signed ranks.

Table 6.3 Tabled Critical Wilcoxon T Values for $n = 10$ Signed Ranks

	$T_{.05}$	$T_{.01}$
Two-tailed values	8	3
One-tailed values	10	5

Since the null hypothesis can only be rejected if the computed value $T = 11$ is equal to or less than the tabled critical value at the prespecified level of significance, we can conclude the following.

In order for the nondirectional alternative hypothesis $H_1: \theta \neq 5$ to be supported, it is irrelevant whether $\Sigma R^+ > \Sigma R^-$ or $\Sigma R^- > \Sigma R^+$. In order for the result to be significant, the computed value of T must be equal to or less than the tabled critical two-tailed value at the prespecified level of significance. Since the computed value $T = 11$ is greater than the tabled critical two-tailed .05 value $T_{.05} = 8$, the nondirectional alternative hypothesis $H_1: \theta \neq 5$ is not supported at the .05 level. It is also not supported at the .01 level, since $T = 11$ is greater than the tabled critical two-tailed .01 value $T_{.01} = 3$.

In order for the directional alternative hypothesis $H_1: \theta > 5$ to be supported, ΣR^+ must be greater than ΣR^- . Since $\Sigma R^+ > \Sigma R^-$, the data are consistent with the directional alternative hypothesis $H_1: \theta > 5$. In order for the result to be significant, the computed value of T must be equal to or less than the tabled critical one-tailed value at the prespecified level of significance. Since the computed value $T = 11$ is greater than the tabled critical one-tailed .05 value $T_{.05} = 10$, the directional alternative hypothesis is not supported at the .05 level. It is also not supported at the .01 level, since $T = 11$ is greater than the tabled critical one-tailed .01 value $T_{.01} = 5$.

In order for the directional alternative hypothesis $H_1: \theta < 5$ to be supported, the following two conditions must be met: a) ΣR^- must be greater than ΣR^+ ; and b) the computed value of T must be equal to or less than the tabled critical one-tailed value at the prespecified level of significance. Since the first of these conditions is not met, the directional alternative hypothesis $H_1: \theta < 5$ is not supported.

A summary of the analysis of Example 6.1 with the **Wilcoxon signed-ranks test** follows: With respect to the median number of times the doctor sees a patient, we can conclude that the data do not indicate that the sample of 10 subjects comes from a population with a median value other than 5.

Except for the fact that the mean rather than the median is employed as the population parameter stated in the null and alternative hypotheses, Example 2.1 is identical to Example 6.1 (i.e., the two examples employ the same set of data). Since Example 2.1 states the null hypothesis with reference to the population mean, it is evaluated with the **single-sample t test**. At this point we will compare the results of the two tests. When the same data are evaluated with the **single-sample t test**, the null hypothesis can be rejected when the directional alternative hypothesis $H_1: \mu > 5$ is employed, but only at the .05 level. With reference to the latter alternative hypothesis, the obtained t value exceeds the tabled critical $t_{.05}$ value by a comfortable margin. When

the **single-sample t test** is employed, the nondirectional alternative hypothesis $H_1: \mu \neq 5$ is not supported at the .05 level.

When Example 6.1 is evaluated with the **Wilcoxon signed-ranks test**, the null hypothesis cannot be rejected regardless of which alternative hypothesis is employed. However, when the directional alternative hypothesis $H_1: \theta > 5$ is employed, the **Wilcoxon signed-ranks test** falls just short of being significant at the .05 level. Directly related to this is the fact that in some sources the tabled critical values published for the Wilcoxon test statistic are not identical to the values listed in **Table A5**. These differences are the result of rounding off protocol. The critical T values in **Table A5** listed for a given level of significance are associated with the probability that is closest to but not greater than the value of alpha. In some instances a T value listed in an alternative table may be one point higher than the value listed in **Table A5**, thus making it easier to reject the null hypothesis. Although these alternative critical values are actually closer to the value of alpha than the values listed in **Table A5**, the probability associated with a tabled critical T value in the alternative table is, in fact, larger than the value of alpha. With reference to Example 6.1, the exact probability associated with $T = 10$ is .0420 (i.e., this represents the likelihood of obtaining a T value of 10 or less). The probability associated with $T = 11$, which is the critical value of T listed in the alternative table, is .0527. Although the latter probability is closer to $\alpha = .05$ than is .0420, it falls above .05. Thus, if one employs the alternative table that contains the tabled critical one-tailed .05 value $T_{.05} = 11$, the alternative hypothesis $H_1: \theta > 5$ is supported at the .05 level. Obviously in a case such as this where the likelihood of obtaining a value equal to or less than the computed value of T is just slightly above .05, it would seem prudent to conduct further studies in order to clarify the status of the alternative hypothesis $H_1: \theta > 5$.

In the case of Examples 6.1 and 2.1, the results of the **Wilcoxon signed-ranks** and **single-sample t test** are fairly consistent for the same set of data. Support for the analogous alternative hypotheses $H_1: \mu > 5$ and $H_1: \theta > 5$ is either clearly indicated (in the case of the t test) or falls just short of significance (in the case of the Wilcoxon test). The slight discrepancy between the two tests reflects the fact that, as a general rule, nonparametric tests are not as powerful as their parametric analogs. In the case of the two tests under consideration, the lower power of the **Wilcoxon signed-ranks test** can be attributed to the loss of information which results from expressing interval/ratio data in a rank-order format (specifically, rank-ordering the difference scores). As noted earlier, when two or more inferential statistical tests are applied to the same set of data and yield contradictory results, it is prudent to replicate the study. In the final analysis, replication is the most powerful tool a researcher has at his disposal for determining the status of a null hypothesis.

VI. Additional Analytical Procedures for the Wilcoxon Signed-Ranks Test and/or Related Tests

1. The normal approximation of the Wilcoxon T statistic for large sample sizes If the sample size employed in a study is relatively large, the normal distribution can be used to approximate the Wilcoxon T statistic. Although sources do not agree on the value of the sample size that justifies employing the normal approximation of the Wilcoxon distribution, they generally state it should be used for sample sizes larger than those documented in the Wilcoxon table contained within the source. Equation 6.2 provides the normal approximation for Wilcoxon T . In the equation T represents the computed value of Wilcoxon T , which for Example 6.1 is $T = 11$. n , as noted previously, represents the number of signed ranks. Thus, in our example, $n = 10$. Note that in the numerator of Equation 6.2, the term $[n(n + 1)]/4$ represents the expected value of T (often summarized with the symbol T_E), which is defined in Section V. The denominator

of Equation 6.2 represents the expected standard deviation of the sampling distribution of the T statistic.

$$z = \frac{T - \frac{n(n+1)}{4}}{\sqrt{\frac{n(n+1)(2n+1)}{24}}} \quad (\text{Equation 6.2})$$

Although Example 6.1 involves only ten signed ranks (a value most sources would view as too small to use with the normal approximation), it will be employed to illustrate Equation 6.2. The reader will see that in spite of employing Equation 6.2 with a small sample size, it will yield essentially the same result as that obtained when the exact table of the Wilcoxon distribution is employed. When the values $T = 11$ and $n = 10$ are substituted in Equation 6.2, the value $z = -1.68$ is computed.

$$z = \frac{11 - \frac{(10)(11)}{4}}{\sqrt{\frac{(10)(11)(21)}{24}}} = -1.68$$

The obtained value $z = -1.68$ is evaluated with **Table A1 (Table of the Normal Distribution)** in the **Appendix**. In **Table A1** the tabled critical two-tailed .05 and .01 values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed .05 and .01 values are $z_{.05} = 1.65$ and $z_{.01} = 2.33$.

Since the smaller of the two values $\Sigma R+$ versus $\Sigma R-$ is selected to represent T , the value of z computed with Equation 6.2 will always be a negative number (unless $\Sigma R+ = \Sigma R-$, in which case z will equal zero). This is the case since, by selecting the smaller value, T will always be less than the expected value T_E . As a result of this, the following guidelines are employed when evaluating the null hypothesis.

a) If a nondirectional alternative hypothesis is employed, the null hypothesis can be rejected if the obtained absolute value of z is equal to or greater than the tabled critical two-tailed value at the prespecified level of significance.

b) When a directional alternative hypothesis is employed, one of the two possible directional alternative hypotheses will be supported if the obtained absolute value of z is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance. Which alternative hypothesis is supported depends on the prediction regarding which of the two values $\Sigma R+$ versus $\Sigma R-$ is larger. The null hypothesis can only be rejected if the directional alternative hypothesis that is consistent with the data is supported.

Employing the above guidelines, when the normal approximation is used with Example 6.1, the following conclusions can be reached.

The nondirectional alternative hypothesis $H_1: \theta \neq 5$ is not supported. This is the case since the computed absolute value $z = 1.68$ is less than the tabled critical two-tailed .05 value $z_{.05} = 1.96$. This decision is consistent with the decision that is reached when the exact table of the Wilcoxon distribution is employed to evaluate the nondirectional alternative hypothesis $H_1: \theta \neq 5$.

The directional alternative hypothesis $H_1: \theta > 5$ is supported at the .05 level. This is the case since the data are consistent with the latter alternative hypothesis (i.e., $\Sigma R+ > \Sigma R-$), and the computed absolute value $z = 1.68$ is greater than the tabled critical one-tailed .05 value $z_{.05} = 1.65$. The directional alternative hypothesis $H_1: \theta > 5$ is not supported at the .01 level,

since the absolute value $z = 1.68$ is less than the tabled critical one-tailed .01 value $z_{.01} = 2.33$. When the exact table of the Wilcoxon distribution is employed, the directional alternative hypothesis $H_1: \theta > 5$ is not supported at the .05 level. However, it was noted that if an alternative table of Wilcoxon critical values is employed, the alternative hypothesis $H_1: \theta > 5$ is supported at the .05 level.

The directional alternative hypothesis $H_1: \theta < 5$ is not supported, since the data are not consistent with the latter alternative hypothesis (which requires that $\Sigma R- > \Sigma R+$).

In closing the discussion of the normal approximation, it should be noted that, in actuality, either $\Sigma R+$ or $\Sigma R-$ can be employed to represent the value of T in Equation 6.2. Either value will yield the same absolute value for z . The smaller of the two values will always yield a negative z value, and the larger of the two values will always yield a positive z value (which in this instance will be $z = 1.68$ if $\Sigma R+ = 44$ is employed in Equation 6.2 to represent T). In evaluating a nondirectional alternative hypothesis, the sign of z is irrelevant. In the case of a directional alternative hypothesis, one must determine whether the data are consistent with the alternative hypothesis that is stipulated. If the data are consistent, one then determines whether or not the absolute value of z is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

2. The correction for continuity for the normal approximation of the Wilcoxon signed-ranks test Although not described in most sources, Marascuilo and McSweeney (1977) employ a correction factor known as the **correction for continuity** for the normal approximation of the Wilcoxon test statistic. The **correction for continuity** is recommended by some sources for use with a number of nonparametric tests that employ a **continuous distribution** (such as the normal distribution) to estimate a **discrete distribution** (such as in this instance the Wilcoxon distribution). As noted in the **Introduction**, in a continuous distribution there are an infinite number of values a variable may assume, whereas in a discrete distribution the number of possible values a variable may assume is limited in number. The correction for continuity is based on the premise that if a continuous distribution is employed to estimate a discrete distribution, such an approximation will inflate the Type I error rate. By employing the correction for continuity, the Type I error rate is ostensibly adjusted to be more compatible with the prespecified alpha value designated by the researcher. When the correction for continuity is applied to a normal approximation of an underlying discrete distribution, it results in a slight reduction in the absolute value computed for z . In the case of the normal approximation of the Wilcoxon test statistic, the correction for continuity requires that .5 be subtracted from the absolute value of the numerator of Equation 6.2. Thus, Equation 6.3 represents the continuity-corrected normal approximation of the Wilcoxon test statistic.

$$z = \frac{\left| T - \frac{n(n+1)}{4} \right| - .5}{\sqrt{\frac{n(n+1)(2n+1)}{24}}} \quad (\text{Equation 6.3})$$

If the correction for continuity is employed with Example 6.1, the value of the numerator of Equation 6.3 is 16, in contrast to the absolute value of 16.5 computed with Equation 6.2. Employing Equation 6.3, the continuity-corrected value $z = 1.63$ is computed. Note that as a result of the absolute value conversion, the numerator of Equation 6.3 will always be a positive number, thus yielding a positive z value.

$$z = \frac{\left| 11 - \frac{(10)(11)}{4} \right| - .5}{\sqrt{\frac{(10)(11)(21)}{24}}} = 1.63$$

Since the absolute value $z = 1.63$ is less than the tabled critical one-tailed .05 value $z_{.05} = 1.65$, the directional hypothesis $H_1: \theta > 5$ is not supported. Note that since the obtained absolute value $z = 1.63$ is slightly below the tabled critical one-tailed value $z_{.05} = 1.65$, it is just short of being significant (in contrast to the continuity-uncorrected absolute value $z = 1.68$ computed with Equation 6.2, which barely achieves significance at the .05 level). The result obtained with $z = 1.63$ is consistent with that obtained employing the exact table of the Wilcoxon distribution. In a case such as this, additional research should be conducted to clarify the status of the null hypothesis, since the issue of whether or not to reject it depends on whether or not one employs the correction for continuity.

3. Tie correction for the normal approximation of the Wilcoxon test statistic Equation 6.4 is an adjusted version of Equation 6.2 that is recommended in some sources (e.g., Daniel (1990) and Marascuilo and McSweeney (1977)) when tied difference scores are present in the data. The tie correction results in a slight increase in the absolute value of z . Unless there are a substantial number of ties, the difference between the values of z computed with Equations 6.2 and 6.4 will be minimal.

$$z = \frac{T - \frac{n(n+1)}{4}}{\sqrt{\frac{n(n+1)(2n+1)}{24} - \frac{\sum t^3 - \sum t}{48}}} \quad \text{(Equation 6.4)}$$

Table 6.4 illustrates the application of the tie correction with Example 6.1.

Table 6.4 Correction for Ties with Normal Approximation			
Subject	Rank	t	t^3
4	1		
6	2		
3	3.5	2	8
5	3.5		
1	5.5	2	8
10	5.5		
2	8	3	27
7	8		
8	8		
9	10		
		$\sum t = 7$	$\sum t^3 = 43$

In the data for Example 6.1 there are three sets of tied ranks: Set 1 involves two subjects (Subjects 3 and 5); Set 2 involves two subjects (Subjects 1 and 10); Set 3 involves three subjects (Subjects 2, 7, and 8). The number of subjects involved in each set of tied ranks represents the values of t in the third column of Table 6.4. The three t values are cubed in the last column of

the table, after which the values Σt and Σt^3 are computed. The appropriate values are now substituted in Equation 6.4.⁶

$$z = \frac{11 - \frac{(10)(11)}{4}}{\sqrt{\frac{(10)(11)(21)}{24} - \frac{43 - 7}{48}}} = -1.69$$

The absolute value $z = 1.69$ is slightly larger than the absolute value $z = 1.68$ obtained without the tie correction. The difference between the two methods is trivial, and in this instance, regardless of which alternative hypothesis is employed, the decision the researcher makes with respect to the null hypothesis is not affected.⁷

Conover (1980, 1999) and Daniel (1990) discuss and/or cite sources on the subject of alternative ways of handling tied difference scores. Conover (1980, 1999) also notes that in some instances, retaining and ranking zero difference scores may actually provide a more powerful test of an alternative hypothesis than the more conventional method employed in this book (which eliminates zero difference scores from the data).

VII. Additional Discussion of the Wilcoxon Signed-Ranks Test

1. Power-efficiency of the Wilcoxon signed-ranks test and the concept of asymptotic relative efficiency Power-efficiency (also referred to as **relative efficiency**) is a statistic that is employed to indicate the power of two tests relative to one another. It is most commonly used in comparing the power of a nonparametric test with its parametric analog. As an example, assume we wish to determine the relative power of the **Wilcoxon signed-ranks test** (designated as Test A) and the **single-sample *t* test** (designated as Test B). Assume that both tests employ the same alpha level with respect to the null hypothesis being evaluated.

For a fixed power value, the statistic PE_{AB} will represent the power-efficiency of Test A relative to Test B. The value of PE_{AB} is computed with Equation 6.5.

$$PE_{AB} = \frac{n_B}{n_A} \quad \text{(Equation 6.5)}$$

Where: n_A is the number of subjects required for Test A and n_B is the number of subjects required for Test B, when each test is required to evaluate an alternative hypothesis at the same power

Thus, if the **single-sample *t* test** requires 95 subjects to evaluate an alternative hypothesis at a power of .80, and the **Wilcoxon signed-ranks test** requires 100 subjects to evaluate the analogous alternative hypothesis at a power of .80, the value of $PE_{AB} = 95/100 = .95$. From this result it can be determined that if 100 subjects are employed to evaluate a null hypothesis with the **single-sample *t* test**, in order to achieve the same level of power for evaluating the analogous null hypothesis with the **Wilcoxon signed-ranks test**, it is necessary to employ $(1/.95)(100) = 105$ subjects.

Conover (1980, 1999) notes that the value computed for **relative efficiency** will be a function of the alpha and beta values a researcher employs in analyzing the data for a study. Pitman (1948) demonstrated that the value of relative efficiency computed for all possible choices of alpha and beta approaches a limiting value as n_A approaches infinity. Pitman referred to this limiting value as the **asymptotic relative efficiency** of the two tests (which is often represented

by the acronym **ARE**, and is also referred to as the **Pitman efficiency**). Since asymptotic relative efficiency is a limiting value that is based on a large sample size, it may not be an accurate metric of efficiency when the sample size employed in a study is relatively small. However, in spite of the latter, for some nonparametric tests, the value computed for asymptotic relative efficiency is achieved with a relatively small sample size. The asymptotic relative efficiency of a test is of practical value, in that if a researcher is selecting among two or more nonparametric tests as an alternative to a parametric test, the nonparametric test with the highest asymptotic relative efficiency will allow for the most powerful test of the alternative hypothesis.

Marascuilo and McSweeney (1977, p. 87) present a table of asymptotic relative efficiency values for a variety of nonparametric tests. In the latter table, asymptotic relative efficiency values are listed in reference to underlying population distributions with different shapes. In the case of the **Wilcoxon signed-ranks test**, its asymptotic relative efficiency is .955 (when contrasted with the **single-sample t test**) when the underlying population distribution is normal. For population distributions that are not normal, the asymptotic relative efficiency of the **Wilcoxon signed-ranks test** is generally equal to or greater than 1. It is interesting to note that when the population distribution is normal, the asymptotic relative efficiency of most nonparametric tests will be less than 1. However, when the underlying population is not normal, it is not uncommon for a nonparametric test to have an asymptotic relative efficiency greater than 1. As a general rule, proponents of nonparametric tests take the position that when a researcher has reason to believe that the normality assumption of the **single-sample t test** has been saliently violated, the **Wilcoxon signed-ranks test** provides a powerful test of the comparable alternative hypothesis.

2. Note on symmetric population concerning hypothesis regarding median and mean Conover (1980, 1999) and Daniel (1990) note that if, in fact, the population from which the sample is derived is symmetrical, the conclusions one draws with regard to the population median are also true with respect to the population mean (since in a symmetrical population the values of the mean and median will be identical). This amounts to saying that if in Example 6.1 we retain (or reject) $H_0: \theta = 5$, we are also reaching the same conclusion with respect to the null hypothesis $H_0: \mu = 5$. There is, however, no guarantee that the results obtained with the **Wilcoxon signed-ranks test** will be entirely consistent with the results derived when the **single-sample t test** is employed to evaluate the same set of data.

3. Confidence interval for the median difference Conover (1980, 1999) describes a procedure (as well as references for alternative procedures) for computing a confidence interval for the median difference for a set of n difference scores.

VIII. Additional Examples Illustrating the Wilcoxon Signed-Ranks Test

With the exception of Examples 1.5 and 1.6, the **Wilcoxon signed-ranks test** can be employed to evaluate a hypothesis about a population median with any of the examples that are employed to illustrate the **single-sample z test (Test 1)** and the **single-sample t test**. As noted in Section I, unless the normality assumption of the aforementioned tests is saliently violated, most researchers would employ a parametric test in lieu of a nonparametric alternative. In all instances in which the **Wilcoxon signed-ranks test** is employed, difference scores are obtained by subtracting the hypothesized value of the population median from each score in the sample. All difference scores are then ranked and evaluated in accordance with the ranking protocol described in Section IV.

Example 6.2 (which is a restatement of Example 6.1 with a different set of data) illustrates the use of the **Wilcoxon signed-ranks test** with the presence of zero difference scores.

Example 6.2 *A physician states that the median number of times he sees each of his patients during the year is five. In order to evaluate the validity of this statement he randomly selects 13 of his patients and determines the number of office visits each of them made during the past year. He obtains the following values for the 13 patients in his sample: 5, 9, 10, 8, 4, 8, 5, 3, 0, 10, 15, 9, 5. Do the data support his contention that the median number of times he sees a patient is five?*

Examination of the data for Example 6.2 reveals that three of the 13 patients visited the doctor five times during the year. Since each of these three scores is equal to the hypothesized value of the population median, they will all produce difference scores of zero. In employing the ranking protocol for the **Wilcoxon signed-ranks test**, all three of these scores will be eliminated from the data analysis. Upon elimination of the three scores, the following ten scores remain: 9, 10, 8, 4, 8, 3, 0, 10, 15, 9. Since the ten remaining scores are identical to the ten scores employed in Example 6.1, the result for Example 6.2 will be identical to that for Example 6.1.

If, on the other hand, the **single-sample t test** is employed to evaluate Example 6.2, all 13 scores are included in the calculations resulting in the value $t = 1.87$,⁸ which is less than the value $t = 1.94$ obtained for Example 2.1 (which employs the 10 scores used in Example 6.1).⁹ The point to be made here is that by not employing the zero difference scores, the same T value is computed for the **Wilcoxon signed-ranks test** for both Examples 6.1 and 6.2. Yet in the case of the **single-sample t test**, which employs all 13 scores for the analysis of Example 6.2, the computed value of t for the latter example is not the same as the computed value of t for Example 2.1 (which employs the same data as Example 6.1). Thus, the presence of zero difference scores may serve to increase the likelihood of a discrepancy between the results obtained with the **Wilcoxon signed-ranks test** and the **single-sample t test**.

Example 6.3 *A college English instructor reads in an educational journal that the median number of times a student is absent from a class that meets for fifty minutes three times a week during a 15 week semester is $\theta = 5$. During the fall semester she keeps a record of the number of times each of the 10 students in her writing class is absent. She obtains the following values: 9, 10, 8, 4, 8, 3, 0, 10, 15, 9. Do the data suggest that the class is representative of a population that has a median of 5?*

Since Example 6.3 employs the same data as Example 6.1, it yields the identical result.

References

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Endnotes

1. Some sources note that one assumption of the **Wilcoxon signed-ranks test** is that the variable being measured is based on a continuous distribution. In practice, however, this assumption is often not adhered to.
2. The **binomial sign test for a single sample** is employed with data that is in the form of a dichotomous variable (i.e., a variable represented by two categories). Each subject's score is assigned to one of the following two categories: Above the value of the hypothesized population median versus Below the value of the hypothesized population median. The test allows a researcher to compute the probability of obtaining the proportion of subjects in each of the two categories, as well as more extreme distributions with respect to the two categories.
3. The **Wilcoxon signed-ranks test** can also be employed in place of the **single-sample z test** when the value of σ is known, but the normality assumption of the latter test is saliently violated.
4. It is just coincidental in this example that the absolute value of some of the difference scores corresponds to the value of the rank assigned to that difference score.
5. The reader should take note of the fact that no critical values are recorded in **Table A5** for very small sample sizes. In the event a sample size is employed for which a critical value is not listed at a given level of significance, the null hypothesis cannot be evaluated at that level of significance. This is the case since with small sample sizes the distribution of ranks will not allow one to generate probabilities equal to or less than the specified alpha value.
6. The term $(\sum t^3 - \sum t)$ in Equation 6.4 can also be written as $\sum_{i=1}^s (t_i^3 - t_i)$. The latter notation indicates the following: a) For each set of ties, the number of ties in the set is subtracted from the cube of the number of ties in that set; and b) the sum of all the values computed in a) is obtained. Thus, in the example under discussion (in which there are $s = 3$ sets of ties):

$$\sum_{i=1}^s (t_i^3 - t_i) = [(2)^3 - 2] + [(2)^3 - 2] + [(3)^3 - 3] = 36$$

The above computed value of 36 is the same as the corresponding value $(\sum t^3 - t) = 43 - 7 = 36$ computed in Equation 6.4 through use of **Table 6.4**.

7. A correction for continuity can be used in conjunction with the tie correction by subtracting .5 from the absolute value computed for the numerator of Equation 6.4. Use of the correction for continuity will reduce the tie-corrected absolute value of z .
8. If the **single-sample t test** is employed with the 13 scores listed for Example 6.2, $\sum X = 91$, $\bar{X} = 91/13 = 7$, and $\sum X^2 = 815$. Thus, $\hat{s} = \sqrt{815 - [(91)^2/13]/(13 - 1)} = 3.85$, $s_{\bar{X}} = 3.85/\sqrt{13} = 1.07$, and $t = (7 - 5)/1.07 = 1.87$.

9. Even though the obtained value $t = 1.87$ is smaller than the value $t = 1.94$ obtained for Example 2.1, it is still significant at the .05 level if one employs the directional alternative hypothesis $H_1: \mu > 5$. This is the case, since for $df = 12$ the tabled critical one-tailed .05 value is $t_{.05} = 1.78$, and $t = 1.87$ exceeds the latter tabled critical value.

Test 7

The Kolmogorov–Smirnov Goodness-of-Fit Test for a Single Sample (Nonparametric Test Employed with Ordinal Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test Does the distribution of n scores that comprise a sample conform to a specific theoretical or empirical population (or probability) distribution?

Relevant background information on test The **Kolmogorov–Smirnov goodness-of-fit test for a single sample** was developed by Kolmogorov (1933). Daniel (1980) notes that because of the similarity between Kolmogorov’s test and a goodness-of-fit test for two independent samples developed by Smirnov (1939) (the **Kolmogorov–Smirnov test for two independent samples (Test 13)**), the test to be discussed is generally referred to as the **Kolmogorov–Smirnov goodness-of-fit test for a single sample**.

The **Kolmogorov–Smirnov goodness-of-fit test for a single sample** is one of a number of goodness-of-fit tests discussed in this book. Goodness-of-fit tests are employed to determine whether the distribution of scores in a sample conforms to the distribution of scores in a specific theoretical or empirical population (or probability) distribution. Goodness-of-fit tests are somewhat unique when contrasted with other types of inferential statistical tests, in that when conducting a goodness-of-fit test a researcher generally wants or expects to retain the null hypothesis. In other words, the researcher wants to demonstrate that a sample is derived from a distribution of a specific type (e.g., a normal distribution). On the other hand, in employing most other inferential tests, a researcher wants or expects to reject the null hypothesis — i.e., the researcher wants or expects to demonstrate that one or more samples do not come from a specific population or from the same population. It should be noted that the alternative hypothesis for a goodness-of-fit test generally does not stipulate an alternative distribution that would become the most likely distribution for the data if the null hypothesis is rejected.

Unlike the **chi-square goodness-of-fit test (Test 8)**, which is discussed in the next chapter, the **Kolmogorov–Smirnov goodness-of-fit test for a single sample** is designed to be employed with a **continuous** variable. (A **continuous variable** is characterized by the fact that a given score can assume any value within the range of values that define the limits of that variable.) The **chi-square goodness-of-fit test**, on the other hand, is designed to be employed with nominal/categorical data involving a **discrete** variable. (A **discrete variable** is characterized by the fact that there are a limited number of values which any score for the variable can assume.) Further clarification of the distinction between discrete and continuous variables can be found in the **Introduction**.

The **Kolmogorov–Smirnov goodness-of-fit test for a single sample** is categorized as a test of ordinal data because it requires that a **cumulative frequency distribution** be constructed (which requires that scores be arranged in order of magnitude). In the **Introduction** it was noted that in a **cumulative frequency distribution**, the cumulative frequency for a given score

represents the frequency of a score plus the frequencies of all scores which are less than that score. Scores are arranged ordinally, with the lowest score at the bottom of the distribution, and the highest score at the top of the distribution. The cumulative frequency for the lowest score will simply be the frequency for that score, since there are no scores below it. On the other hand, the cumulative frequency for the highest score will always equal n , the total number of scores in the distribution. In some instances a cumulative frequency distribution may present cumulative proportions (which can also be expressed as probabilities) or cumulative percentages in lieu of and/or in addition to cumulative frequencies. A cumulative proportion or percentage for a given score represents the proportion or percentage of scores that are equal to or less than that score. When the term cumulative probability is employed, it means the likelihood of obtaining a given score or any score below it (which is numerically equivalent to the cumulative proportion for that score). Table 7.1 represents a cumulative frequency distribution for a distribution comprised of $n = 20$ scores. Each of the scores that occur in the distribution are listed in the first column. Note that in the third column of Table 7.1, the cumulative frequency values are obtained by adding to the frequency of a score in a given row the frequencies of all scores that fall below it. A cumulative proportion for a score is obtained by dividing the cumulative frequency of the score by n . A cumulative proportion is converted into a cumulative percentage by moving the decimal point for the proportion two places to the right.

Table 7.1 Cumulative Frequency Distribution

X	Frequency (f)	Cumulative frequency	Cumulative proportion	Cumulative percentage
15	3	20	$20/20 = 1$	100%
14	2	17	$17/20 = .85$	85%
13	2	15	$15/20 = .75$	75%
12	0	13	$13/20 = .65$	65%
11	4	13	$13/20 = .65$	65%
10	2	9	$9/20 = .45$	45%
9	1	7	$7/20 = .35$	35%
8	0	6	$6/20 = .30$	30%
7	4	6	$6/20 = .30$	30%
6	2	2	$2/20 = .10$	10%
$n = 20$				

In the example to be presented for the **Kolmogorov–Smirnov goodness-of-fit test for a single sample**, a cumulative frequency distribution will be constructed. However, the table containing the cumulative frequency distribution of the test data (Table 7.2) will list the scores in reverse order from that listed in Table 7.1 (i.e., in Table 7.2 the lowest score will be at the top and the highest score at the bottom). This alternative way of arranging the cumulative frequencies is commonly employed to summarize the data analysis for **Kolmogorov–Smirnov goodness-of-fit test for a single sample**.

II. Example

Example 7.1 *A researcher conducts a study to evaluate whether the distribution of the length of time it takes migraine patients to respond to a 100 mg. dose of an intravenously administered drug is normal, with a mean response time of 90 seconds and a standard deviation of 35 seconds (i.e., $\mu = 90$ and $\sigma = 35$). The amount of time (in seconds) that elapses between the administration of the drug and cessation of a headache for 30 migraine patients is recorded below. The 30 scores are arranged ordinally (i.e., from fastest response time to slowest response time).*

21, 32, 38, 40, 48, 55, 63, 66, 70, 75, 80, 84, 86, 90, 90, 93, 95, 98, 100, 105, 106, 108, 115, 118, 126, 128, 130, 142, 145, 155

Do the data conform to a normal distributions with the specified parameters?

III. Null versus Alternative Hypotheses

Prior to reading the null and alternative hypotheses to be presented in this section, the reader should be take note of the following: a) The protocol for the **Kolmogorov–Smirnov goodness-of-fit test for a single sample** requires that a cumulative probability distribution be constructed for both the sample distribution and the hypothesized population distribution. The test statistic is defined by the point that represents the greatest vertical distance at any point between the two cumulative probability distributions; and b) Within the framework of the null and alternative hypotheses, the notation $F(X)$ represents the population distribution from which the sample distribution is derived, while the notation $F_o(X)$ represents the hypothesized theoretical or empirical distribution with respect to which the sample distribution is being evaluated for goodness-of-fit. Alternatively, $F(X)$ can be conceptualized as representing the cumulative probability distribution for the population from which the sample is derived, and $F_o(X)$ as the cumulative probability distribution for the hypothesized population.

Null hypothesis $H_0: F(X) = F_o(X)$ for all values of X

(The distribution of data in the sample is consistent with the hypothesized theoretical population distribution. In terms of the parameters stipulated in Example 7.1, the null hypothesis is stating that the sample data are derived from a normal distribution, with $\mu = 90$ and $\sigma = 35$. Another way of stating the null hypothesis is as follows: At no point is the greatest vertical distance between the sample cumulative probability distribution (which is assumed to be the best estimate of the cumulative probability distribution of the population from which the sample is derived) and the hypothesized cumulative probability distribution larger than what would be expected by chance, if the sample is derived from the hypothesized distribution.)

Alternative hypothesis $H_1: F(X) \neq F_o(X)$ for at least one value of X

(The distribution of data in the sample is inconsistent with the hypothesized theoretical population distribution. In terms of the parameters stipulated in Example 7.1, the null hypothesis is stating that the sample data are not derived from a normal distribution, with $\mu = 90$ and $\sigma = 35$. An alternative way of stating this alternative hypothesis is as follows: There is at least one point where the greatest vertical distance between the sample cumulative probability distribution (which is assumed to be the best estimate of the cumulative probability distribution of the population from which the sample is derived) and the hypothesized cumulative probability distribution is larger than what would be expected by chance, if the sample is derived from the hypothesized distribution. At the point of maximum deviation separating the two distributions, the cumulative probability for the sample distribution is either significantly greater or less than the cumulative probability for the hypothesized distribution. This is a **nondirectional alternative hypothesis** and it is evaluated with a **two-tailed test**.)

or

$H_1: F(X) > F_o(X)$ for at least one value of X

(The distribution of data in the sample is inconsistent with the hypothesized theoretical population

distribution. In terms of the parameters stipulated in Example 7.1, the null hypothesis is stating that the sample data are not derived from a normal distribution, with $\mu = 90$ and $\sigma = 35$. The latter is the case, since there is at least one point at which the vertical distance between the sample cumulative probability distribution (which is assumed to be the best estimate of the cumulative probability distribution of the population from which the sample is derived) and the hypothesized cumulative probability distribution is larger than what would be expected by chance, if the sample is derived from the hypothesized distribution. At the point of maximum deviation separating the two distributions, the cumulative probability for the sample distribution is significantly greater than the cumulative probability for the hypothesized distribution. This is a **directional alternative hypothesis** and it is evaluated with a **one-tailed test**.)

or

$$H_1: F(X) < F_o(X) \text{ for at least one value of } X$$

(The distribution of data in the sample is inconsistent with the hypothesized theoretical population distribution. In terms of the parameters stipulated in Example 7.1, the null hypothesis is stating that the sample data are not derived from a normal distribution, with $\mu = 90$ and $\sigma = 35$. The latter is the case, since there is at least one point at which the vertical distance between the sample cumulative probability distribution (which is assumed to be the best estimate of the cumulative probability distribution of the population from which the sample is derived) and the hypothesized cumulative probability distribution is larger than what would be expected by chance, if the sample is derived from the hypothesized distribution. At the point of maximum deviation separating the two distributions, the cumulative probability for the sample distribution is significantly less than the cumulative probability for the hypothesized distribution. This is a **directional alternative hypothesis** and it is evaluated with a **one-tailed test**.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis is rejected.

IV. Test Computations

As noted in Sections I and III, the test protocol for the **Kolmogorov–Smirnov goodness-of-fit test for a single sample** requires that the cumulative probability distribution for the sample data be contrasted with the cumulative probability distribution for the hypothesized population. [Table 7.2](#) summarizes the steps that are involved in conducting the analysis.

The values represented in the columns of [Table 7.2](#) are summarized below.

The values of the response time scores of the 30 subjects in the sample (i.e., the X scores) are recorded in **Column A**. There are 29 rows corresponding to each of the scores (with two subjects having obtained the identical score of 90).

Each value in **Column B** is the z score (i.e., a standard deviation score) that results when the X score in a given row is substituted in the equation $z = (X - \mu)/\sigma$ (which is Equation I.27), where $\mu = 90$ and $\sigma = 35$. Thus, for each row, the equation $z = (X - 90)/35$ is employed. To illustrate, in the case of **Row 1**, where $X = 21$, the value $z = (21 - 90)/35 = -1.97$ is computed. In the case of the last row, where $X = 155$, the value $z = (155 - 90)/35 = 1.86$ is computed. Note that a negative z value will be obtained for any X score below the mean, and a positive z value for any X score above the mean.

Each value in **Column C** represents the proportion of cases in the normal distribution that falls between the population mean and the z score computed for the X score in a given row (i.e., the z value computed in **Column B**). To illustrate, in the case of **Row 1**, where $X = 21$ and

Table 7.2 Calculation of Test Statistic for Kolmogorov–Smirnov Goodness-of-Fit Test for a Single Sample

A (X)	B (z)	C (p)	D ($F_o(X_i) = p \pm .50$)	E ($S(X_i)$)	F ($ S(X_i) - F_o(X_i) $)	G ($ S(X_{i-1}) - F_o(X_i) $)
21	-1.97	.4756	.0244	1/30 = .0333	.0089	0-.0244 = .0244
32	-1.66	.4515	.0485	2/30 = .0667	.0182	.0333-.0485 = .0152
38	-1.49	.4319	.0681	3/30 = .1000	.0319	.0667-.0681 = .0014
40	-1.43	.4236	.0764	4/30 = .1333	.0569 = M	.1000-.0764 = .0236
48	-1.20	.3849	.1151	5/30 = .1667	.0516	.1333-.1151 = .0182
55	-1.00	.3413	.1587	6/30 = .2000	.0413	.1667-.1587 = .0080
63	-.77	.2794	.2206	7/30 = .2333	.0127	.2000-.2206 = .0206
66	-.69	.2549	.2451	8/30 = .2667	.0216	.2333-.2451 = .0118
70	-.57	.2157	.2843	9/30 = .3000	.0157	.2667-.2843 = .0176
75	-.43	.1664	.3336	10/30 = .3333	.0003	.3000-.3336 = .0336
80	-.29	.1141	.3859	11/30 = .3667	.0192	.3333-.3859 = .0526
84	-.17	.0675	.4325	12/30 = .4000	.0325	.3667-.4325 = .0658
86	-.11	.0438	.4562	13/30 = .4333	.0229	.4000-.4562 = .0562
90	.00	.0000	.5000	15/30 = .5000	.0000	.4333-.5000 = .0667 = M'
93	.09	.0359	.5359	16/30 = .5333	.0026	.5000-.5359 = .0359
95	.14	.0557	.5557	17/30 = .5667	.0110	.5333-.5557 = .0224
98	.23	.0901	.5901	18/30 = .6000	.0099	.5667-.5901 = .0234
100	.29	.1141	.6141	19/30 = .6333	.0192	.6000-.6141 = .0141
105	.43	.1664	.6664	20/30 = .6667	.0003	.6333-.6664 = .0331
106	.46	.1772	.6772	21/30 = .7000	.0228	.6667-.6772 = .0105
108	.51	.1950	.6950	22/30 = .7333	.0383	.7000-.6950 = .0050
115	.71	.2611	.7611	23/30 = .7667	.0056	.7333-.7611 = .0278
118	.80	.2881	.7881	24/30 = .8000	.0119	.7667-.7881 = .0214
126	1.03	.3485	.8485	25/30 = .8333	.0152	.8000-.8485 = .0485
128	1.09	.3621	.8621	26/30 = .8667	.0046	.8333-.8621 = .0288
130	1.14	.3729	.8729	27/30 = .9000	.0271	.8667-.8729 = .0062
142	1.48	.4306	.9306	28/30 = .9333	.0027	.9000-.9306 = .0306
145	1.57	.4418	.9418	29/30 = .9667	.0249	.9333-.9418 = .0085
155	1.86	.4686	.9686	30/30 = 1.0000	.0314	.9667-.9686 = .0019

$z = -1.97$, the proportion .4756 in **Column C** (which is the entry for $z = -1.97$ in **Column 2** of **Table A1 (Table of the Normal Distribution)** in the **Appendix**) is the proportion cases in the normal distribution between the mean and a z score of -1.97 . In the case of the last row, where $X = 155$ and $z = 1.86$, the proportion .4686 in **Column C** is the proportion cases in the normal distribution between the mean and a z score of 1.86.

Each value in **Column D** represents the cumulative proportion for a given X score (and its associated z score) in the hypothesized theoretical distribution (i.e., in a normal distribution with $\mu = 90$ and $\sigma = 35$). To put it another way, if the decimal point is moved two places to the right, the value in **Column D** represents the percentile rank of a given X score in the hypothesized theoretical distribution. For any X score for which a negative z score is computed, the proportion in **Column D** can be obtained by subtracting from .5000 the proportion in **Column C** for that score (it will also correspond to the proportion for that z score in **Column 3** of **Table A1**). For any X score for which a positive z score is computed, the proportion in **Column D** can be obtained by adding .5000 to the proportion in **Column C** for that score (i.e., it will correspond to the sum of .5000 and the proportion for that z score in **Column 2** of **Table A1**). To illustrate, in the case of **Row 1**, where $X = 21$ and $z = -1.97$, the proportion .0244 is equal to $.5000 - .4756 = .0244$. In the case of the last row, where $X = 155$ and $z = 1.86$, the proportion .9686 is equal to $.5000 + .4686 = .9686$. The values in **Column D** are commonly represented by the notation $F_o(X_i)$, where the subscript i represents the i^{th} score/row in **Table 7.2**.

Each value in **Column E** represents the cumulative proportion for a given X score (and its associated z score) in the sample distribution. To illustrate, in the case of **Row 1**, where $X = 21$, its cumulative proportion is its cumulative frequency (1) divided by the total number of scores in the sample ($n = 30$). Thus, $1/30 = .0333$. In the case of the score $X = 100$, its cumulative proportion in the sample distribution is 19 (i.e., a score of 100 is equal to or greater than 19 of the 30 scores). Thus, its cumulative proportion is $19/30 = .6333$. In the case of the score $X = 155$ in the last row, its cumulative frequency in the sample distribution is 30 (since it is the highest score). Thus, its cumulative proportion is $30/30 = 1$. The values in **Column E** are commonly represented by the notation $S(X_i)$, where the subscript i represents the i^{th} score/row in [Table 7.2](#).

Each value in **Column F** is the absolute value of the difference between the proportions in **Column E** and **Column D** — in other words, the difference between the proportions in the sample distribution and the hypothesized population distribution. Thus, $F_i = |E_i - D_i|$ or $F_i = |S(X_i) - F_o(X_i)|$. To illustrate, in the case of **Row 1**, where $D_i = F_o(X_i) = .0244$ and $E_i = S(X_i) = .0333$, we compute the value $F_i = .0089$ as follows.

$$F_i = |E_i - D_i| = |S(X_i) - F_o(X_i)| = |.0333 - .0244| = .0089$$

In the case of the row where $X = 100$, and where $D_i = F_o(X_i) = .6141$ and $E_i = S(X_i) = .6333$, we compute the value $F = .0192$ as follows:

$$F_i = |E_i - D_i| = |S(X_i) - F_o(X_i)| = |.6333 - .6141| = .0192$$

In the case of the last row where $X = 155$, and where $D_i = F_o(X_i) = .9686$ and $E_i = S(X_i) = 1$, we compute the value $F_i = .0314$ as follows:

$$F_i = |E_i - D_i| = |S(X_i) - F_o(X_i)| = |1 - .9686| = .0314$$

As noted in Section III, the test statistic for the **Kolmogorov–Smirnov goodness-of-fit test for a single sample** is defined by the greatest vertical distance at any point between the two cumulative probability distributions. The largest absolute value obtained in **Column F** will represent that value. In [Table 7.2](#) the largest absolute value is .0569, which is designated as the test statistic (represented by the notation M).

Each value in **Column G** is the absolute value of the difference between the proportion in **Column D** for a given row (i.e., $F_o(X_i)$) and the proportion in **Column E** for the preceding row (i.e., $S(X_{i-1})$). In other words, $G_i = |E_{i-1} - D_i|$ or $G_i = |S(X_{i-1}) - F_o(X_i)|$. To illustrate, in the case of **Row 1**, where $D_i = F_o(X_i) = .0244$ and $E_i = S(X_{i-1}) = 0$, we compute the value $G_i = .0244$ as noted below. Note that the value 0 is employed to represent the initial value of $E_{i-1} = S(X_{i-1})$, since that is the value that .0333 is added to in order to get the entry .0333 in **Row 1** of **Column E**.

$$G_i = |E_{i-1} - D_i| = |S(X_{i-1}) - F_o(X_i)| = |0 - .0244| = .0244$$

In the case of the row where $X = 100$, and where $D_i = F_o(X_i) = .6141$ and $E_{i-1} = S(X_{i-1}) = .6000$, we compute the value $G_i = .0141$ as follows:

$$G_i = |E_{i-1} - D_i| = |S(X_{i-1}) - F_o(X_i)| = |.6000 - .6141| = .0141$$

In the case of the last row where $X = 155$, and where $D_i = F_o(X_i) = .9686$ and $E_{i-1} = S(X_{i-1}) = .9667$, we compute the value $G_i = .0019$ as follows:

$$G_i = |E_{i-1} - D_i| = |S(X_{i-1}) - F_o(X_i)| = |.9667 - .9686| = .0019$$

As noted above, the test statistic for the **Kolmogorov–Smirnov goodness-of-fit test for a single sample** is defined by the greatest vertical distance at any point between the two cumulative probability distributions. However, when that value is determined mathematically through use of the value in **Column F**, it is still possible that the largest vertical distance may occur **at some point between one of the scores in the sample distribution**. Since it is assumed that the variable being evaluated is continuous, if there is a larger vertical distance for some score other than those in the sample, the latter score should represent the test statistic, instead of the M value recorded in **Column F**. The method for determining whether there is a larger vertical distance than the maximum value recorded in **Column F** is to compute the values in **Column G** of [Table 7.2](#). If the largest value computed in **Column G** (designated M') is larger than the M value computed in **Column F**, then M' is employed to represent the test statistic. In [Table 7.2](#), the largest value is .0667, and thus $M' = .0667$ becomes our test statistic.¹

An alternative method for determining the largest vertical distance is to draw a graph which depicts: a) The curve of the hypothesized cumulative probability distribution, and b) The points that represent the cumulative probabilities for the sample distribution (which if connected would result in a curve of the cumulative probabilities for the sample distribution). Through use of such a graph a determination can be made with respect to whether there is a larger vertical distance at some point on the two cumulative probability distributions than the distance/value computed for M in **Column F**. The graphical method is described in Conover (1980, 1999), Daniel (1990), and Sprent (1993). If such a graph is constructed for Example 7.1, most of the points for the cumulative sample distribution fall above the curve of the hypothesized cumulative probability distribution (with the value $M = .0569$ representing the vertical distance of one of those points above the latter curve). However, some of the points, including the one resulting in the value $M' = .0667$, fall below the curve of the hypothesized cumulative probability distribution.

V. Interpretation of the Test Results

The test statistic for the **Kolmogorov–Smirnov goodness-of-fit test for a single sample** is the larger of the two values M or M' . The test statistic is evaluated with [Table A21](#) (**Table of Critical Values for the Kolmogorov–Smirnov Goodness-of-Fit Test for a Single Sample**) in the **Appendix**. If at any point along the two cumulative probability distributions the greatest distance (i.e., the larger of the two values M or M') is equal to or greater than the tabled critical value recorded in [Table A21](#), the null hypothesis is rejected. The critical values in [Table A21](#) are listed in reference to sample size. For $n = 30$, the tabled critical two-tailed .05 and .01 values are $M_{.05} = .242$ and $M_{.01} = .290$, and the tabled critical one-tailed .05 and .01 values are $M_{.05} = .218$ and $M_{.01} = .270$.

The following guidelines are employed in evaluating the null hypothesis for the **Kolmogorov–Smirnov goodness-of-fit test for a single sample**.

a) If the nondirectional alternative hypothesis $H_1: F(X) \neq F_o(X)$ is employed, the null hypothesis can be rejected if the computed value of the test statistic is equal to or greater than the tabled critical two-tailed M value at the prespecified level of significance.

b) If the directional alternative hypothesis $H_1: F(X) > F_o(X)$ is employed, the null hypothesis can be rejected if the computed value of the test statistic is equal to or greater than the tabled critical one-tailed M value at the prespecified level of significance. Additionally, the difference between the two cumulative probability distributions must be such that, in reference to the point that represents the test statistic, the cumulative probability associated with the sample distribution is larger than the cumulative probability associated with the hypothesized population

distribution. In other words, if, instead of computing an absolute value in **Columns F and G** of [Table 7.2](#), we retain the sign of the difference, then a positive sign is required for the directional alternative hypothesis $H_1: F(X) > F_o(X)$ to be supported. Thus, if M is the largest vertical distance, $S(X_i) > F_o(X_i)$, and if M' is the largest vertical distance, $S(X_{i-1}) > F_o(X_i)$.

c) If the directional alternative hypothesis $H_1: F(X) < F_o(X)$ is employed, the null hypothesis can be rejected if the larger of the two values M versus M' is equal to or greater than the tabled critical one-tailed M value at the prespecified level of significance. Additionally, the difference between the two cumulative probability distributions must be such that in reference to the point that represents the test statistic, the cumulative probability associated with the sample distribution is smaller than the cumulative probability associated with the hypothesized population distribution. In other words, if, instead of computing an absolute value in **Columns F and G** of [Table 7.2](#), we retain the sign of the difference, then a negative sign is required for the directional alternative hypothesis $H_1: F(X) < F_o(X)$ to be supported. Thus, if M is the largest vertical distance, $S(X_i) < F_o(X_i)$, and if M' is the largest vertical distance, $S(X_{i-1}) < F_o(X_i)$.

The above guidelines will now be employed in reference to the computed test statistic $M' = .0667$.

a) If the nondirectional alternative hypothesis $H_1: F(X) \neq F_o(X)$ is employed, the null hypothesis cannot be rejected, since $M' = .0667$ is less than the tabled critical two-tailed values $M_{.05} = .242$ and $M_{.01} = .290$.

b) If the directional alternative hypothesis $H_1: F(X) < F_o(X)$ is employed, the null hypothesis cannot be rejected since $M' = .0667$ is less than the tabled critical one-tailed values $M_{.05} = .218$ and $M_{.01} = .270$. This is the case in spite of the fact that the test statistic is consistent with the latter alternative hypothesis (i.e., since $[F_o(X_i) = .5000] > [S(X_{i-1}) = .4333]$, if the sign is taken into account, the computed value of M' is a negative value: $M' = S(X_{i-1}) - F_o(X_i) = .4333 - .5000 = -.0667$).

c) If the directional alternative hypothesis $H_1: F(X) > F_o(X)$ is employed, the null hypothesis cannot be rejected, since, for the latter alternative hypothesis to be supported, the cumulative proportion for the sample distribution must be larger than the cumulative proportion for the hypothesized population distribution.

A summary of the analysis of Example 7.1 with the **Kolmogorov–Smirnov goodness-of-fit test for a single sample** follows: The data are consistent with the null hypothesis that the sample is derived from a normally distributed population, with $\mu = 90$ and $\sigma = 35$.

VI. Additional Analytical Procedures for the Kolmogorov–Smirnov Goodness-of-Fit Test for a Single Sample

1. Computing a confidence interval for the Kolmogorov–Smirnov goodness-of-fit test for a single sample Daniel (1990) describes how to construct a confidence interval for the cumulative distribution for the sample proportions.² The confidence interval computed for the **Kolmogorov–Smirnov test** statistic is comprised of two sets of limits — a set of **upper limits** and a set of **lower limits**. The reference points for determining the latter values are the $S(X_i)$ scores in **Column E** of [Table 7.2](#). Equation 7.1 is the general equation for computing the limits that define a confidence interval at any point along the cumulative probability distribution for the sample.

$$CI_{(1-\alpha)} = S(X_i) \pm (M_{\alpha/2}) \quad \text{(Equation 7.1)}$$

Where: $M_{\alpha/2}$ represents the tabled critical two-tailed M value for a given value of n , below which a proportion (percentage) equal to $[1 - (\alpha/2)]$ of the cases falls. If the

proportion (percentage) of the distribution that falls within the confidence interval is subtracted from 1 (100%), it will equal the value of α .

The **upper limits** for the confidence interval are computed by adding the relevant critical value to each of the values of $S(X_i)$ in **Column E** of [Table 7.2](#). If any of the resulting values is greater than 1, the upper limit for that $S(X_i)$ value is set equal to 1, since a probability cannot be greater than 1. In the case of Example 7.1, 29 upper limit values will be computed, each value corresponding to one of the 29 $S(X_i)$ values recorded in the rows of [Table 7.2](#).

The **lower limits** for the confidence interval are computed by subtracting the relevant critical value from each of the values of $S(X_i)$ in **Column E** of [Table 7.2](#). If any of the resulting values is less than 0, the lower limit for that $S(X_i)$ value is set equal to 0, since a probability cannot be less than 0. In the case of Example 7.1, 29 lower limit values will be computed, each value corresponding to one of the 29 $S(X_i)$ values recorded in the rows of [Table 7.2](#).

The above methodology will now be described in reference to Example 7.1. Let us assume we wish to compute a 95% confidence interval for the cumulative probability distribution of the population from which the sample is derived. Since we are interested in the 95% confidence interval, the value that will be employed for $M_{\alpha/2}$ in Equation 7.1 will be the tabled critical two-tailed .05 M value, which as previously noted is $M_{.05} = .242$. Thus, we will add to and subtract .242 from each of the $S(X_i)$ values in **Column E** of [Table 7.2](#).

To illustrate, the first $S(X_i)$ value (associated with the score of $X = 21$) is .0333. When .242 is added to the latter value we obtain .2753, which is the upper limit for that point on the cumulative probability distribution. When .242 is subtracted from .0333 we obtain the value $-.2087$. Since the latter value is less than zero, we set the lower limit at that point equal to zero.

In the case of the score of $X = 90$, the value of $S(X_i)$ is .5000. When .242 is added to the latter value we obtain .7420, which is the upper limit for that point on the cumulative probability distribution. When .242 is subtracted from .5000 we obtain .2580, which is the lower limit for that point on the cumulative probability distribution.

In the case of the score of $X = 155$, the value of $S(X_i)$ is 1. When .242 is added to the latter value we obtain 1.242. Since the latter value is greater than 1, we set the upper limit at that point equal to 1. When .242 is subtracted from 1 we obtain .7580, which is the lower limit for that point on the cumulative probability distribution.

As noted earlier, the above described procedure is employed for all 29 points on the cumulative probability distribution for the sample. The resulting set of upper and lower limits defines the confidence interval.

2. The power of the Kolmogorov–Smirnov goodness-of-fit test for a single sample Books that discuss the **Kolmogorov–Smirnov goodness-of-fit test for a single sample** do not describe specific procedures for computing the power of the test. Conover (1980, 1999), Daniel (1990), and Hollander and Wolfe (1999) cite sources that discuss the power of the test and/or describe procedures for determining power. Daniel (1980) and Zar (1999) note that when the **Kolmogorov–Smirnov goodness-of-fit test for a single sample** is employed with grouped data (i.e., scores are categorized in class intervals instead of evaluating each score separately), the test becomes overly conservative (i.e., the power of the test is reduced). Zar (1999) presents a correction factor for the **Kolmogorov–Smirnov test statistic**, endorsed by Harter *et al.* (1984) and Khamis (1990), which can increase the power of the test. Zar (1999) also states that the **Kolmogorov–Smirnov test** is more powerful than the **chi-square goodness-of-fit test** under the following conditions: a) When the sample size is small; and b) When the expected frequencies for the **chi-square test** are small.

3. Test 7a: The Lilliefors test for normality Massey (1951) notes that when the population parameters (e.g., μ and σ) are not known beforehand, but are instead estimated from the sample data, the result yielded by the **Kolmogorov–Smirnov goodness-of-fit test for a single sample** tends to be overly conservative (i.e., the statistical power of the test is less than its power when the values of the parameters are known). Various sources (Conover (1980, 1999) and Daniel (1990)) describe Lilliefors (1967, 1969, 1973) extension of the **Kolmogorov–Smirnov goodness-of-fit test for a single sample** to circumstances in which the values of the population parameters for a variety of distributions (e.g., normal, exponential, gamma) and not known, and thus have to be estimated from the sample data.³ The procedure to be described here, which is designed to assess goodness-of-fit for a normal distribution when one or both of the population parameters μ and σ are unknown, is referred to as the **Lilliefors test for normality**. The test procedure for the **Lilliefors test for normality** is identical to that described for the **Kolmogorov–Smirnov goodness-of-fit test for a single sample**, except for the following: a) The values of the sample mean (\bar{X}) and estimated population standard deviation (\tilde{s}) are employed to represent the mean and standard deviation of the hypothesized population distribution. Thus, the values of \bar{X} and \tilde{s} are employed to compute the z values in **Column B** of **Table 7.2**; and b) Instead of obtaining the critical values from **Table A21**, the values documented in **Table A22 (Table of Critical Values for the Lilliefors Test for Normality)** in the **Appendix** are employed.⁴ As is the case with employing the critical values in **Table A21**, in order to reject the null hypothesis when the test statistic is based on the **Lilliefors test for normality**, the computed value for M or M' (i.e., which ever of the two is larger) must be equal to or greater than the tabled critical value in **Table A22** at the prespecified level of significance. The values recorded in **Table A22** are only applicable when both the values of μ and σ are unknown, and must be estimated from the sample data.

Table 7.3 reevaluates the data for Example 7.1 employing the values for the sample mean ($\bar{X} = 90.07$) and estimated population standard deviation ($\tilde{s} = 34.79$) in place of the values $\mu = 90$ and $\sigma = 35$ employed for the **Kolmogorov–Smirnov goodness-of-fit test for a single sample**. The values $\bar{X} = 90.07$ and $\tilde{s} = 34.79$ were computed by employing Equations I.1 and I.8 with the 30 scores in Example 7.1.

In **Table 7.3** the computed values for M and M' in **Columns F** and **G** are $M = .0594$ and $M' = .0667$. Since the values $\bar{X} = 90.07$ and $\tilde{s} = 34.79$ are quite close to the values $\mu = 90$ and $\sigma = 35$ employed for the **Kolmogorov–Smirnov goodness-of-fit test for a single sample**, it is not surprising that the values in the rows of **Table 7.3** are quite close and, in some cases, identical to the values in the rows of **Table 7.2**. The values $M = .0594$ and $M' = .0667$ obtained in **Table 7.3** are either very close or identical to the values $M = .0569$ and $M' = .0667$ obtained in **Table 7.2** for the **Kolmogorov–Smirnov goodness-of-fit test for a single sample**. Since $M' = .0667$ is larger than $M = .0594$, $M' = .0667$ will represent the test statistic for the **Lilliefors test for normality**.

As is the case with **Table A21**, the critical values listed in **Table A22** are listed in reference to sample size. Lilliefors' (1967) table only contains two-tailed .40, .30, .20, .10, and .02 values, and one-tailed .20, .15, .10, .05, and .01 values. Daniel (1990) employs more detailed tables for the **Lilliefors test** statistic developed by Mason and Bell (1986). The latter tables have slightly different critical values than those listed in **Table A22**. Mason and Bell's (1986) tables also have additional critical values for when μ is unknown and σ is known, and for when μ is known and σ is unknown.

Employing **Table A22** for $n = 30$, it can be seen that the tabled critical one-tailed .05 and .01 values (which correspond to the two-tailed .10 and .02 critical values) are $M_{.05} = .161$ and $M_{.01} = .187$. Since $M' = .0667$ is less than both of the aforementioned critical values, the null hypothesis of normality cannot be rejected. From the magnitude of the critical values, it is

Table 7.3 Calculation of Test Statistic for the Lilliefors Test for Normality

A (X)	B (z)	C (p)	D ($F_o(X_i) = p \pm .50$)	E $S(X_i)$	F $ S(X_i) - F_o(X_i) $	G $ S(X_{i-1}) - F_o(X_i) $
21	-1.99	.4761	.0239	1/30 = .0333	.0094	0-.0239 = .0239
32	-1.67	.4525	.0475	2/30 = .0667	.0192	.0333-.0475 = .0142
38	-1.50	.4332	.0668	3/30 = .1000	.0332	.0667-.0668 = .0001
40	-1.44	.4251	.0749	4/30 = .1333	.0594 = M	.1000-.0749 = .0251
48	-1.21	.3869	.1131	5/30 = .1667	.0536	.1333-.1131 = .0202
55	-1.01	.3438	.1562	6/30 = .2000	.0438	.1667-.1562 = .0105
63	-.78	.2823	.2177	7/30 = .2333	.0156	.2000-.2177 = .0177
66	-.69	.2549	.2451	8/30 = .2667	.0216	.2333-.2451 = .0118
70	-.58	.2190	.2810	9/30 = .3000	.0190	.2667-.2810 = .0143
75	-.43	.1664	.3336	10/30 = .3333	.0003	.3000-.3336 = .0336
80	-.29	.1141	.3859	11/30 = .3667	.0192	.3333-.3859 = .0526
84	-.17	.0675	.4325	12/30 = .4000	.0325	.3667-.4325 = .0658
86	-.12	.0478	.4522	13/30 = .4333	.0189	.4000-.4522 = .0522
90	.00	.0000	.5000	15/30 = .5000	.0000	.4333-.5000 = .0667 = M'
93	.08	.0319	.5319	16/30 = .5333	.0014	.5000-.5319 = .0319
95	.14	.0557	.5557	17/30 = .5667	.0110	.5333-.5557 = .0224
98	.23	.0901	.5901	18/30 = .6000	.0099	.5667-.5901 = .0234
100	.29	.1141	.6141	19/30 = .6333	.0192	.6000-.6141 = .0141
105	.43	.1664	.6664	20/30 = .6667	.0003	.6333-.6664 = .0331
106	.46	.1772	.6772	21/30 = .7000	.0228	.6667-.6772 = .0105
108	.52	.1985	.6985	22/30 = .7333	.0348	.7000-.6985 = .0015
115	.72	.2642	.7642	23/30 = .7667	.0025	.7333-.7642 = .0309
118	.80	.2881	.7881	24/30 = .8000	.0119	.7667-.7881 = .0214
126	1.03	.3485	.8485	25/30 = .8333	.0152	.8000-.8485 = .0485
128	1.09	.3621	.8621	26/30 = .8667	.0046	.8333-.8621 = .0288
130	1.15	.3749	.8749	27/30 = .9000	.0251	.8667-.8749 = .0082
142	1.49	.4319	.9319	28/30 = .9333	.0014	.9000-.9319 = .0319
145	1.58	.4429	.9429	29/30 = .9667	.0238	.9333-.9429 = .0096
155	1.87	.4693	.9693	30/30 = 1.0000	.0307	.9667-.9693 = .0026

obvious that if more detailed tables were available listing the two-tailed .05 and .01 critical values, the latter values would be greater than the value $M' = .0667$, and thus the result would not be significant. Since the test statistic is interpreted in the same way as the **Kolmogorov–Smirnov test** statistic, the conclusion drawn from the **Lilliefors test for normality** is identical to that reached with the **Kolmogorov–Smirnov test**. Thus, the null hypothesis of normality is retained.

VII. Additional Discussion of the Kolmogorov–Smirnov Goodness-of-Fit Test for a Single Sample

1. Effect of sample size on the result of a goodness-of-fit test Conover (1980, 1999) notes that if one employs a large enough sample size, almost any goodness-of-fit test will result in rejection of the null hypothesis. In view of the latter, Conover (1980, 1999) states that in order to conclude on the basis of a goodness-of-fit test that data conform to a specific distribution, the data should be reasonably close to the specifications of the distribution. Thus, in some cases where a large sample size is involved, a researcher may end up rejecting the null hypothesis of goodness-of-fit for a hypothesized distribution, yet in spite of the latter, if the sample data are reasonably close to the hypothesized distribution, one can probably operate on the assumption that the sample data provide an adequate fit for the hypothesized distribution.

2. The Kolmogorov–Smirnov goodness-of-fit test for a single sample versus the chi-square goodness-of-fit test and alternative goodness-of-fit tests Daniel (1980) discusses the relative merits of employing the **Kolmogorov–Smirnov goodness-of-fit test for a single sample** for assessing goodness-of-fit versus the **chi-square goodness-of-fit test**. In his discussion Daniel (1980) notes the following: a) Whereas the **Kolmogorov–Smirnov test** is designed for use with continuous data, the **chi-square goodness-of-fit test** is designed to be used with discrete data; b) The **Kolmogorov–Smirnov test** is able to evaluate a one-tailed hypothesis regarding goodness-of-fit, while the **chi-square test** is not suited for such an analysis; c) The **Kolmogorov–Smirnov test** allows for the computation of a confidence interval for the cumulative population distribution the sample represents, whereas the **chi-square test** does not allow the latter computation; d) Since the **chi-square test** groups data into categories/class intervals, it does not use as much information as the **Kolmogorov–Smirnov test**, which generally evaluates each score separately; and e) The **chi-square test** provides an approximation of an exact sampling distribution (the multinomial distribution), whereas the sampling distribution employed by the **Kolmogorov–Smirnov test** is exact.

Although the **Kolmogorov–Smirnov test for a single sample** and the **chi-square goodness-of-fit test** are the most commonly employed (as well as discussed) tests for goodness-of-fit, a number of other goodness-of-fit tests have been developed (including the following which are described in this book: The **single sample test for evaluating population skewness (Test 4)**, the **single sample test for evaluating population kurtosis (Test 5)**, and the **D’Agostino–Pearson test of normality (Test 5a)**). Among the other goodness-of-fit tests that are described and/or discussed in nonparametric statistics books are **David’s empty cell test** (David (1950)), the **Cramér–von Mises goodness-of-fit test** (attributed to Cramér (1928), von Mises (1931), and Smirnov (1936)), and the **Shapiro–Wilk test for normality** (Shapiro and Wilk (1965, 1968)) (which is described in Conover (1980, 1999)). Daniel (1990) contains a comprehensive discussion of alternative goodness-of-fit procedures.

The general subject of goodness-of-fit tests for randomness is discussed in Section VII of the **single-sample runs tests (Test 10)**. **Autocorrelation**, which a procedure that can also be employed for assessing goodness-of-fit for randomness, is discussed in Section VII of the **Pearson product–moment correlation coefficient**.

VIII. Additional Example Illustrating the Kolmogorov–Smirnov Goodness-of-fit Test for a Single Sample

Example 7.2 *The results of an intelligence test administered to 30 students are evaluated with respect to goodness-of-fit for a normal distribution with the following parameters: $\mu = 90$ and $\sigma = 35$. The IQ scores of the 30 students are noted below.*

21, 32, 38, 40, 48, 55, 63, 66, 70, 75, 80, 84, 86, 90, 90, 93, 95, 98, 100, 105, 106, 108, 115, 118, 126, 128, 130, 142, 145, 155

Do the data conform to a normal distributions with the specified parameters?

Since Example 7.2 employs the same data as Example 7.1, it yields the identical result.

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Endnotes

1. a) Marascuilo and McSweeney (1977) employ a modified protocol that can result in a larger absolute value for M in **Column F** or M' in **Column G** than the one obtained in [Table 7.2](#). The latter protocol employs a separate row in the table for each instance in which the same score occurs more than once in the sample data. If the latter protocol were employed in [Table 7.2](#), there would be two rows in the table for the score of 90 (which is the only score that occurs more than once). The first 90 would be recorded in **Column A** in a row that has a cumulative proportion in **Column E** equal to $14/30 = .4667$. The second 90 would be recorded in the following row in **Column A** with a cumulative proportion in **Column E** equal to $15/30 = .5000$. In the case of Example 7.1, the outcome of the analysis would not be affected if the aforementioned protocol is employed. In some instances, however, it can result in a different/larger M or M' value. The protocol employed by Marascuilo and McSweeney (1977) is employed by sources who argue that when there are ties present in the data (i.e., a score occurs more than once), the protocol described in this chapter (which is used in most sources) results in an overly conservative test (i.e., makes it more difficult to reject a false null hypothesis); b) It is not necessary to compute the values in **Column G** if a discrete variable is being evaluated. Conover (1980, 1999) and Daniel (1990) discuss the use of the **Kolmogorov–Smirnov goodness-of-fit test for a single sample** with discrete data. Studies cited in the latter sources indicate that when the **Kolmogorov–Smirnov test** is employed with discrete data, it yields an overly conservative result (i.e., the power of the test is reduced).
2. A general discussion of confidence intervals can be found in Section VI of the **single sample t test (Test 2)**.
3. The gamma and exponential distributions are continuous probability distributions.
4. [Table A22](#) is only appropriate for assessing goodness-of-fit for a normal distribution. Lilliefors (1969, 1973) has developed tables for other distributions (e.g., the exponential and gamma distributions).

Test 8

The Chi-Square Goodness-of-Fit Test (Nonparametric Test Employed with Categorical/Nominal Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test In the underlying population represented by a sample are the observed cell frequencies different from the expected cell frequencies?

Relevant background information on test The **chi-square goodness-of-fit test**, also referred to as the **chi-square test for a single sample**, is employed in a hypothesis testing situation involving a single sample. Based on some preexisting characteristic or measure of performance, each of n observations (subjects/objects) that is randomly selected from a population consisting of N observations (subjects/objects) is assigned to one of k mutually exclusive categories.¹ The data are summarized in the form of a table consisting of k cells, each cell representing one of the k categories. Table 8.1 summarizes the general model for the **chi-square goodness-of-fit test**. In Table 8.1, C_i represents the i^{th} cell/category and O_i represents the number of observations in the i^{th} cell. The number of observations recorded in each cell of the table is referred to as the **observed frequency** of a cell.

Table 8.1 General Model for Chi-Square Goodness-of-Fit Test

	Total number of observations					
Cell/Category	C_1	C_2	\cdots	C_i	\cdots	C_k
Observed frequency	O_1	O_2	\cdots	O_i	\cdots	O_k

The experimental hypothesis evaluated with the **chi-square goodness-of-fit test** is whether or not there is a difference between the **observed frequencies** of the k cells and their **expected frequencies** (also referred to as the **theoretical frequencies**). The expected frequency of a cell is determined through the use of probability theory or is based on some preexisting empirical information about the variable under study. If the result of the **chi-square goodness-of-fit test** is significant, the researcher can conclude that in the underlying population represented by the sample there is a high likelihood that the observed frequency for at least one of the k cells is not equal to the expected frequency of the cell. It should be noted that, in actuality, the test statistic for the **chi-square goodness-of-fit test** provides an approximation of a binomially distributed variable (when $k = 2$) and a multinomially distributed variable (when $k > 2$). The larger the value of n , the more accurate the chi-square approximation of the **binomial** and **multinomial distributions**.²

The **chi-square goodness-of-fit test** is based on the following assumptions: a) Categorical/nominal data are employed in the analysis. This assumption reflects the fact that the test data should represent frequencies for k mutually exclusive categories; b) The data that are evaluated

consist of a random sample of n independent observations. This assumption reflects the fact that each observation can only be represented once in the data; and c) The expected frequency of each cell is 5 or greater. When this assumption is violated, it is recommended that if $k = 2$, the **binomial sign test for a single sample (Test 9)** be employed to evaluate the data. When the expected frequency of one or more cells is less than 5 and $k > 2$, the multinomial distribution should be employed to evaluate the data. The reader should be aware of the fact that sources are not in agreement with respect to the minimum acceptable value for an expected frequency. Many sources employ criteria suggested by Cochran (1952), who stated that none of the expected frequencies should be less than 1 and that no more than 20% of the expected frequencies should be less than 5. However, many sources suggest the latter criteria may be overly conservative. In the event that a researcher believes that one or more expected cell frequencies are too small, two or more cells can be combined with one another to increase the values of the expected frequencies. The latter procedure is demonstrated and discussed in Section VI.

Zar (1999, p. 470) provides an interesting discussion on the issue of the lowest acceptable value for an expected frequency. Within the framework of his discussion, Zar (1999) cites studies indicating that when the **chi-square goodness-of-fit test** is employed to evaluate a hypothesis regarding a **uniform distribution**, the test is extremely **robust**. A **robust test** is one that still provides reliable information in spite of the fact that one or more of its assumptions have been violated. A **uniform distribution** (also referred to as a **rectangular distribution**) is one in which each of the possible values a variable can assume has an equal likelihood of occurring. In the case of an analysis involving the **chi-square goodness-of-fit test**, a distribution is uniform if each of the cells has the same expected frequency.

II. Examples

Two examples will be employed to illustrate the use of the **chi-square goodness-of-fit test**. Since the two examples employ identical data, they will result in the same conclusions with respect to the null hypothesis.

Example 8.1 *A die is rolled 120 times in order to determine whether or not it is fair (unbiased). The value 1 appears 20 times, the value 2 appears 14 times, the value 3 appears 18 times, the value 4 appears 17 times, the value 5 appears 22 times, and the value 6 appears 29 times. Do the data suggest that the die is biased?*

Example 8.2 *A librarian wishes to determine if it is equally likely that a person will take a book out of the library each of the six days of the week the library is open (assume the library is closed on Sundays). She records the number of books signed out of the library during one week and obtains the following frequencies: Monday, 20; Tuesday, 14; Wednesday, 18; Thursday, 17; Friday, 22; and Saturday, 29. Assume no person is permitted to take out more than one book during the week. Do the data indicate there is a difference with respect to the number of books taken out on different days of the week?*

III. Null versus Alternative Hypotheses

In the statement of the null and alternative hypotheses, the lower case Greek letter **omicron** (\omicron) is employed to represent the observed frequency of a cell in the underlying population, and the lower case Greek letter **epsilon** (ϵ) is employed to represent the expected frequency of the cell in the population. Thus, \omicron_i and ϵ_i , respectively, represent the observed and expected frequency of the i^{th} cell in the underlying population. With respect to the observed and expected fre-

quencies for the sample data, the notation O_i is employed to represent the observed frequency of a cell, and E_i the expected frequency of a cell.

Null hypothesis H_0 : $O_i = E_i$ for all cells.

(In the underlying population the sample represents, for each of the k cells, the observed frequency of a cell is equal to the expected frequency of the cell. With respect to the sample data this leads to the prediction that for all k cells $O_i = E_i$.)

Alternative hypothesis H_i : $O_i \neq E_i$ for at least one cell.

(In the underlying population the sample represents, for at least one of the k cells the observed frequency of a cell is not equal to the expected frequency of the cell. With respect to the sample data this leads to the prediction that for at least one cell $O_i \neq E_i$. The reader should take note of the fact that the alternative hypothesis does not state that in order to reject the null hypothesis there must be a discrepancy between the observed and expected frequencies of all k cells. Rejection of the null hypothesis can be the result of a discrepancy between the observed and expected frequencies for one cell, two cells, ..., $(k - 1)$ cells, or all k cells. As a general rule, sources always state the alternative hypothesis for the **chi-square goodness-of-fit test** nondirectionally. Although the latter protocol will be adhered to in this book, in actuality it is possible to state the alternative hypothesis directionally. The issue of the directionality of alternative hypothesis is discussed in Section VII.)

IV. Test Computations

Table 8.2 summarizes the data and computations for Examples 8.1 and 8.2.

Table 8.2 Chi-square Summary Table for Examples 8.1 and 8.2

Cell	O_i	E_i	$(O_i - E_i)$	$(O_i - E_i)^2$	$\frac{(O_i - E_i)^2}{E_i}$
1/Monday	20	20	0	0	0
2/Tuesday	14	20	-6	36	1.8
3/Wednesday	18	20	-2	4	.2
4/Thursday	17	20	-3	9	.45
5/Friday	22	20	2	4	.2
6/Saturday	29	20	9	81	4.05
$\Sigma O_i = 120$		$\Sigma E_i = 120$	$\Sigma(O_i - E_i) = 0$		$\chi^2 = 6.7$

In Table 8.2, the observed frequency of each cell (O_i) is listed in Column 2, and the expected frequency of each cell (E_i) is listed in Column 3. The computations for the **chi-square goodness-of-fit test** require that the observed and expected cell frequencies be compared with one another. In order to determine the expected frequency of a cell one must either: a) Employ the appropriate theoretical probability for the test model; or b) Employ a probability that is based on existing empirical data.

In Examples 8.1 and 8.2, computation of the expected cell frequencies is based on the theoretical probabilities for the test model.³ Specifically, if the die employed in Example 8.1 is fair, it is equally likely that in a given trial any one of the six face values will appear. Thus, it follows that each of the six face values should occur one-sixth of the time. The probability associated with each of the possible outcomes (represented by the notation π , which is the lower

case Greek letter **π**) can be computed as follows: $\pi = r/k$ (**where:** r represents the number of outcomes that will allow an observation to be placed in a specific category, and k represents the total number of possible outcomes in any trial). Since, in each trial only one face value will result in an observation being assigned to any one of the six categories, the value of the numerator for each of the six categories will equal 1. Since in each trial there are six possible outcomes, the value of the denominator for each of the six categories will equal six. Thus, for each category, $\pi_i = 1/6$.⁴ Note that the sum of the k probabilities must equal 1, since if the value $1/6$ is added six times it sums to 1 (i.e., $\sum_{i=1}^k \pi_i = 1$).

The same logic employed for Example 8.1 can be applied to Example 8.2. If it is equally likely that a person will take a book out of the library on any one of the six days of the week the library is open, it is logical to predict that on each day of the week one-sixth of the books will be taken out. Consequently, the value $1/6$ will represent the expected probability for each of the six cells in Example 8.2. The expected frequency of each cell in Examples 8.1 and 8.2 is computed by multiplying the total number of observations by the probability associated with the cell. Equation 8.1 summarizes the computation of an expected frequency.

$$E_i = (n)(\pi_i) \quad \text{(Equation 8.1)}$$

Where: n represents the total number of observations

π_i represents the probability that an observation will fall within the i^{th} cell

Since in both Example 8.1 and 8.2 the total number of observations is $n = 120$, the expected frequency for each cell can be computed as follows: $E_i = (120)(1/6) = 20$.

Upon determining the expected cell frequencies, Equation 8.2 is employed to compute the test statistic for the **chi-square goodness-of-fit test**.

$$\chi^2 = \sum_{i=1}^k \left[\frac{(O_i - E_i)^2}{E_i} \right] \quad \text{(Equation 8.2)}$$

The operations described by Equation 8.2 are as follows: a) The expected frequency of each cell is subtracted from its observed frequency. This is summarized in Column 4 of [Table 8.2](#); b) For each cell, the difference between the observed and expected frequency is squared. This is summarized in Column 5 of [Table 8.2](#); c) For each cell, the squared difference between the observed and expected frequency is divided by the expected frequency of the cell. This is summarized in Column 6 of [Table 8.2](#); and d) The value of chi-square is computed by summing all of the values in Column 6. For both Examples 8.1 and 8.2, Equation 8.2 yields the value $\chi^2 = 6.7$.

Note that in [Table 8.2](#) the sums of the observed and expected frequencies are identical. This must always be the case, and any time these sums are not equivalent it indicates that a computational error has been made.⁵ It is also required that the sum of the differences between the observed and expected frequencies equals zero (i.e., $\sum(O_i - E_i) = 0$). Any time the latter value does not equal zero, it indicates an error has been made. Since all of the $(O_i - E_i)$ values are squared in Column 5, the sum of Column 6, which represents the value of χ^2 , must always be a positive number. If a negative value is obtained for chi-square, it indicates an error has been made. The only time χ^2 will equal zero is when $O_i = E_i$ for all k cells.

V. Interpretation of the Test Results

The obtained value $\chi^2 = 6.7$ is evaluated with **Table A4 (Table of the Chi-Square Distribution)** in the **Appendix**. A general overview of the chi-square distribution and guidelines for interpreting the values in **Table A4** can be found in Sections I and V of the **single-sample chi-square test for a population variance (Test 3)**.

The degrees of freedom that are employed in evaluating the results of the **chi-square goodness-of-fit test** are computed with Equation 8.3.⁶

$$df = k - 1 \quad (\text{Equation 8.3})$$

When **Table A4** is employed to evaluate a chi-square value computed for the **chi-square goodness-of-fit test**, the following protocol is employed. The tabled critical values for the **chi-square goodness-of-fit test** are always derived from the right tail of the distribution. Thus, the tabled critical .05 chi-square value (to be designated $\chi^2_{.05}$) will be the tabled chi-square value at the 95th percentile. In the same respect, the tabled critical .01 chi-square value (to be designated $\chi^2_{.01}$) will be the tabled chi-square value at the 99th percentile. The general rule is that the tabled critical chi-square value for a given level of alpha will be the tabled chi-square value at the percentile that corresponds to the value of $(1 - \alpha)$. In order to reject the null hypothesis, the obtained value of chi-square must be equal to or greater than the tabled critical value at the pre-specified level of significance. The aforementioned guidelines for determining tabled critical chi-square values are employed when the alternative hypothesis is stated nondirectionally (which, as noted earlier, is usually the case). The determination of tabled critical chi-square values in reference to a directional alternative hypothesis is discussed in Section VII.

Applying the guidelines for a nondirectional analysis to Examples 8.1 and 8.2, the degrees of freedom are computed to be $df = 6 - 1 = 5$. The tabled critical .05 chi-square value for $df = 5$ is $\chi^2_{.05} = 11.07$, which, as noted above, is the tabled chi-square value at the 95th percentile. The tabled critical .01 chi-square value for $df = 5$ is $\chi^2_{.01} = 15.09$, which, as noted above, is the tabled chi-square value at the 99th percentile. Since the computed value $\chi^2 = 6.7$ is less than $\chi^2_{.05} = 11.07$, the null hypothesis cannot be rejected at the .05 level. This result can be summarized as follows: $\chi^2 (5) = 6.7, p > .05$. Although there are some deviations between the observed and expected frequencies in **Table 8.2**, the result of the **chi-square goodness-of-fit test** indicates there is a reasonably high likelihood that the deviations in the sample data can be attributed to chance.

A summary of the analysis of Examples 8.1 and 8.2 with the **chi-square goodness-of-fit test** follows: a) In Example 8.1 the data do not suggest that the die is biased; and b) In Example 8.2 the data do not suggest that there is any difference with respect to the number of books that are taken out of the library on different days of the week.

VI. Additional Analytical Procedures for the Chi-Square Goodness-of-Fit Test and/or Related Tests

1. Comparisons involving individual cells when $k > 2$ Within the framework of the **chi-square goodness-of-fit test** it is possible to compare individual cells with one another. To illustrate this, assume that we wish to address the following questions in reference to Examples 8.1 and 8.2.

a) In Example 8.1, is the observed frequency of 29 for the face value 6 higher than the combined observed frequency of the other five face values? Note that this is not the same thing as asking whether the face value 6 is more likely to occur when compared individually with any

of the other five face values. In order to answer the latter question, the observed frequency for the face value 6 must be contrasted with the observed frequency for the specific face value in which one is interested.

b) In Example 8.2, is the observed frequency of 29 books for Saturday higher than the combined observed frequency of the other five days of the week? Note that this is not the same thing as asking whether a person is more likely to take a book out of the library on Saturday when compared individually with any one of the other five days of the week. In order to answer the latter question, the observed frequency for Saturday must be contrasted with the observed frequency of the specific day of the week in which one is interested.

In order to answer the question of whether **6/Saturday** occurs a disproportionate amount of the time, the observed frequency for **6/Saturday** must be contrasted with the combined observed frequencies of the other five face values/days of the week. In order to do this, the original six-cell chi-square table is collapsed into a two-cell table, with one cell representing **6/Saturday** (Cell 1) and the other cell representing **1, 2, 3, 4, 5/M, T, W, Th, F** (Cell 2). The expected frequency of Cell 1 remains $\pi_1 = 1/6$, since if we are dealing with a random process, there is still a one in six chance that in any trial the face value 6 will occur, or that a person will take a book out of the library on Saturday. Thus: $E_1 = (120)(1/6) = 20$. The expected frequency of Cell 2 is computed as follows: $E_2 = (120)(5/6) = 100$. Note that the probability $\pi_2 = 5/6$ for Cell 2 is the sum of the probabilities of the other five cells. In other words, if it is randomly determined what face value appears on the die or on what day of the week a person takes a book out of the library, there is a five in six chance that a face value other than 6 will appear on any role of the die, and a five in six chance that a book is taken out of the library on a day of the week other than Saturday. [Table 8.3](#) summarizes the data for the problem under discussion.

Table 8.3 Chi-Square Summary Table When $\pi_1 = 1/6$ and $\pi_2 = 5/6$

Cell	O_i	E_i	$(O_i - E_i)$	$(O_i - E_i)^2$	$\frac{(O_i - E_i)^2}{E_i}$
6/Saturday	29	20	9	81	4.05
1,2,3,4,5/M,T,W,Th,F	91	100	-9	81	.81
	$\Sigma O_i = 120$	$\Sigma E_i = 120$	$\Sigma(O_i - E_i) = 0$		$\chi^2 = 4.86$

Since there are $k = 2$ cells, $df = 2 - 1 = 1$. Employing [Table A4](#) for $df = 1$, $\chi^2_{.05} = 3.84$ and $\chi^2_{.01} = 6.63$. Since the obtained value $\chi^2 = 4.86$ is larger than $\chi^2_{.05} = 3.84$, the null hypothesis can be rejected at the .05 level (i.e., $\chi^2 (1) = 4.86, p < .05$). The null hypothesis cannot be rejected at the .01 level since $\chi^2 = 4.86 < \chi^2_{.01} = 6.63$. Note that by stating the problem in reference to one face value or one day of the week, the researcher is able to reject the null hypothesis at the .05 level. Recollect that the analysis in Section V does not allow the researcher to reject the null hypothesis.⁷

If the original null hypothesis a researcher intends to study deals with the frequency of **Cell 6/Saturday** versus the other five cells, the researcher is not obliged to defend the analysis described above. However, let us assume that the original null hypothesis under study is the one stipulated in Section III. Let us also assume that upon evaluating the data, the null hypothesis cannot be rejected. Because of this the researcher then decides to reconceptualize the problem as summarized in [Table 8.3](#). To go even further, the researcher can extend the type of analysis depicted in [Table 8.3](#) to all six cells (i.e., compare the observed frequency of each of the cells with the combined observed frequency of the other five cells — e.g., **Cell 1/Monday** versus **Cells**

2, 3, 4, 5, 6/T, W, Th, F, S, as well as **Cell 2/Tuesday** versus **Cell 1, 3, 4, 5, 6/M, W, Th, F, S**, and so on for the other three cells). If $\alpha = .05$ is employed for each of the six comparisons, the overall likelihood of committing at least one Type I error within the set of six comparisons will be substantially above .05 (to be exact, it will equal $1 - (1 - .05)^6 = .26$). If within the set of six comparisons the researcher does not want more than a 5% chance of committing a Type I error, it is required that the alpha level employed for each comparison be adjusted. Specifically, by employing a probability of $.05/6 = .0083$ per comparison, the researcher will insure that the overall Type I error rate will not exceed 5%. It should be noted however, that by employing a smaller alpha level per comparison, the researcher is reducing the power associated with each comparison. A detailed discussion of the protocol for adjusting the alpha level when conducting multiple comparisons can be found in Section VI of the **single-factor between-subjects analysis of variance (Test 21)**.

It should also be noted that a researcher can reduce the number of degrees of freedom employed in a chi-square analysis by reconfiguring a table comprised of three or more cells into a table comprised of fewer cells. Reduction of the degrees of freedom will increase the likelihood of rejecting the null hypothesis, since the lower the value of the degrees of freedom, the lower the tabled critical chi-square value at a given level of significance. By employing the latter strategy, a researcher may be able convert a table with three or more cells which does not yield a significant result into a smaller table that does yield a significant result. Obviously, it would be inappropriate to employ such a strategy if its sole purpose is to milk a significant result out of a set of data. Any significant results obtained within the latter context have to be viewed with extreme caution, and should be replicated prior to being submitted for publication.

It is also possible to conduct other comparisons in addition to the ones noted above. For example one can compare the observed frequencies for face values/days of the week **1, 2, 3/M, T, W** with the observed frequencies for **4, 5, 6/Th, F, S**. In such an instance there again will be two cells, with a probability of $\pi_i = 1/2$ for each cell (since $\pi_i = 3/6 = 1/2$). A researcher can also break down the original six cell table into three cells — e.g., **1, 2/M, T** versus **3, 4/W, Th** versus **5, 6/F, S**. In this instance, the probability for each cell will equal $\pi_i = 1/3$ (since $\pi_i = 2/6 = 1/3$).

Another type of comparison that can be conducted is to contrast just two of the original six cells with one another. Specifically, let us assume we want to compare **Cell 1/Monday** with **Cell 2/Tuesday**. [Table 8.4](#) is employed to summarize the data for such a comparison.

Table 8.4 Chi-Square Summary Table for Comparison

Cell	O_i	E_i	$(O_i - E_i)$	$(O_i - E_i)^2$	$\frac{(O_i - E_i)^2}{E_i}$
1/Monday	20	17	3	9	.53
2/Tuesday	14	17	3	9	.53
$\Sigma O_i = 34$		$\Sigma E_i = 34$	$\Sigma(O_i - E_i) = 0$		$\chi^2 = 1.06$

Note that in the above example, since we employ only two cells, the probability for each cell will be $\pi_i = 1/2$. The expected frequency of each cell is obtained by multiplying $\pi_i = 1/2$ by the total number of observations in the two cells (which equals 34). As noted previously, in conducting a comparison such as the one above, a critical issue the researcher must address is what value of alpha to employ in evaluating the null hypothesis. If $\alpha = .05$ is used, for $df = 1$, $\chi^2_{.05} = 3.84$. The null hypothesis cannot be rejected, since the obtained value $\chi^2 = 1.06 < \chi^2_{.05} = 3.84$.

A major point that has been emphasized throughout the discussion in this section is that, depending upon how one initially conceptualizes a problem, there will generally be a number of different ways in which a set of data can be analyzed. Furthermore, after analyzing the full set of data, additional comparisons involving two or more categories can be conducted. The various types of comparisons that one can conduct can either be planned or unplanned. The term **planned comparison** is employed throughout the book to refer to a comparison that is planned prior to the data collection phase of a study. In contrast, an **unplanned comparison** is one that a researcher decides to conduct after the experimental data have been collected and scrutinized. A problem associated with unplanned comparisons is that in a large body of data there are a potentially large number of comparisons that can be conducted. Consequently, a researcher can conduct many comparisons until one or more of them yield a significant result. The latter strategy can thus be employed to milk significant results out of a large body of data. It was noted earlier in this section that the larger the number of comparisons one conducts, the greater the likelihood that any significant result obtained for a given comparison will be a Type I error (as opposed to a genuine difference that can be reliably replicated).

Whenever possible comparisons should be planned, and most sources take the position that when a researcher plans a limited number of comparisons before the data collection phase of a study, one is not obliged to control the overall Type I error rate. However, when comparisons are not planned, most sources believe that some adjustment of the Type I error rate should be made in order to avoid inflating it excessively. As noted earlier in this section, one way of achieving the latter is to divide the maximum overall Type I error rate one is willing to tolerate by the total number of comparisons one conducts. The resulting probability value will represent the alpha level employed in evaluating each of the comparisons. A comprehensive discussion of the subject of comparisons (which is also germane to the issue of alternate ways of conceptualizing a set of data) can be found in Section VI of the **single-factor between-subjects analysis of variance**.

In closing the discussion of comparisons for the **chi-square goodness-of-fit test**, it should be noted that some sources present alternative comparison procedures that may yield results that are not in total agreement with those obtained in this section. In instances where different methodologies yield substantially different results (which will usually not be the case), a replication study evaluating the same hypothesis is in order. As noted throughout the book, replication is the most effective way to demonstrate the validity of a hypothesis. Obviously, the use of large sample sizes in both original and replication studies further increases the likelihood of obtaining reliable results. An alternative approach for conducting comparisons is presented in the next section.

2. The analysis of standardized residuals An alternative procedure for conducting comparisons (developed by Haberman (1973) and cited in sources such as Siegel and Castellan (1988)) involves the computation of **standardized residuals**. By computing the latter values, one is able to determine which cells are the major contributors to a significant chi-square value. Equation 8.4 is employed to compute a standardized residual (R_i) for each cell in a chi-square table.

$$R_i = \frac{(O_i - E_i)}{\sqrt{E_i}} \quad \text{(Equation 8.4)}$$

A value computed for a residual (which is interpreted as a normally distributed variable) is evaluated with **Table A1 (Table of the Normal Distribution)** in the **Appendix**. Any residual with an absolute value that is equal to or greater than the tabled critical two-tailed .05 value $z_{.05} = 1.96$ is significant at the .05 level. Any residual with an absolute value that is equal to or greater than the tabled critical two-tailed .01 value $z_{.01} = 2.58$ is significant at the .01 level. Any cell in a chi-square table which has a significant residual makes a significant contribution to

the obtained chi-square value. For any cell that has a significant residual, one can conclude that the observed frequency of the cell differs significantly from its expected frequency. The sign of the standardized residual indicates whether the observed frequency of the cell is above (+) or below (–) the expected frequency. The sum of the squared residuals for all k cells will equal the obtained value of chi-square. Although the result of the chi-square analysis for Examples 8.1 and 8.2 is not significant, the standardized residuals for the chi-square table are computed and summarized in [Table 8.5](#).

Table 8.5 Analysis of Residuals for Examples 8.1 and 8.2

Cell	O_i	E_i	$(O_i - E_i)$	$R_i = \frac{(O_i - E_i)^2}{\sqrt{E_i}}$	$R_i^2 = \left[\frac{(O_i - E_i)}{\sqrt{E_i}} \right]^2$
1/Monday	20	20	0	0	0
2/Tuesday	14	20	–6	–1.34	1.80
3/Wednesday	18	20	–2	–.45	.20
4/Thursday	17	20	–3	–.67	.45
5/Friday	22	20	2	.45	.20
6/Saturday	29	20	9	2.01	4.05
$\Sigma O_i = 120 \quad \Sigma E_i = 120 \quad \Sigma(O_i - E_i) = 0$					$\chi^2 = 6.7$

Note that the only cell with a standardized residual with an absolute value above 1.96 is **Cell 6/Saturday**. Thus, one can conclude that the observed frequency of **Cell 6/Saturday** is significantly above its expected frequency and, as such, the cell would be viewed as a major contributor in obtaining a significant chi-square value (if, in fact, the computed chi-square value had been significant). It should be noted that this result is consistent with the first comparison that was conducted in the previous section, since the latter comparison indicates that the observed frequency of 29 for **Cell 6/Saturday** deviates significantly from its expected frequency, when the cell is contrasted with the combined frequencies of the other five cells.

3. Computation of a confidence interval for the chi-square goodness-of-fit test The procedure to be described in this section allows one to compute a confidence interval for the proportion of cases in the underlying population that falls within any cell in a one-dimensional chi-square table.⁸ The true population proportion for a cell will be represented by the notation π_i . The procedure to be described below is a large sample approximation of the confidence interval for a binomially distributed variable (which applies to the **chi-square goodness-of-fit test** model when $k = 2$). The analysis to be described in this section will assume that if $k > 2$, the original chi-square table is converted into a table consisting of two cells.

Equation 8.5 is the general equation for computing a confidence interval for a population proportion for a specific cell, when there are $k = 2$ cells

$$\left[p_1 - z_{(\alpha/2)} \sqrt{\frac{p_1 p_2}{n}} \right] \leq \pi_1 \leq \left[p_1 + z_{(\alpha/2)} \sqrt{\frac{p_1 p_2}{n}} \right] \quad \text{(Equation 8.5)}$$

Where: p_1 represents the proportion of observations in Cell 1. In the analysis under discussion, Cell 1 will represent the single cell whose observed frequency is being compared with the combined observed frequencies of the remaining five cells. The value of p_1 is computed by dividing the number of observations in Cell 1 (which will be

represented by the notation x) by n (which represents the total number of observations). Thus, $p_1 = x/n$.

$p_2 = 1 - p_1$ The value p_2 represents the proportion of observations in Cell 2. In the analysis under discussion, Cell 2 will represent the combined frequencies of the other five cells. p_2 can be computed by dividing the number of observations that are not in Cell 1 by the total number of observations. Thus, $p_2 = (n - x)/n$.

$z_{\alpha/2}$ represents the tabled critical value in the normal distribution below which a proportion (percentage) equal to $[1 - (\alpha/2)]$ of the cases falls. If the proportion (percentage) of the distribution that falls within the confidence interval is subtracted from 1 (100%), it will equal the value of α .

If one wants to determine the 95% confidence interval, the tabled critical two-tailed .05 value $z_{.05} = 1.96$ is employed in Equation 8.5. The tabled critical two-tailed .01 value $z_{.01} = 2.58$ is employed to compute the 99% confidence interval. The value $\sqrt{(p_1 p_2)/n}$ in Equation 8.5 represents the estimated standard error of the population proportion. The latter value is an estimated standard deviation of a sampling distribution of a proportion.

If (as is done in Table 8.3) the data for Examples 8.1 and 8.2 are expressed in a format consisting of two cells, Equation 8.5 can be employed to compute a confidence interval for each of the six cells. Thus, if we wish to compute a confidence interval for the **Cell 6/Saturday** we can determine that $p_1 = x/n = 29/120 = .242$ and $p_2 = (n-x)/n = (120 - 29)/120 = .758$. Substituting the latter values and the value $z_{.05} = 1.96$ in Equation 8.5, the 95% confidence interval is computed below.

$$.242 - (1.96) \sqrt{\frac{(.242)(.758)}{120}} \leq \pi_1 \leq .242 + (1.96) \sqrt{\frac{(.242)(.758)}{120}}$$

$$\pi_1 = .242 \pm .077$$

$$.165 \leq \pi_1 \leq .319$$

Thus, the researcher can be 95% confident that the true proportion of cases in the underlying population that falls in **Cell 6/Saturday** is a value between .165 and .319. Stated in probabilistic terms, there is a probability/likelihood of .95 that the true value of the population proportion falls within the range .165 to .319.

The 99% confidence interval, which has a larger range, is computed below by employing $z_{.01} = 2.58$ in Equation 8.5.

$$.242 - (2.58) \sqrt{\frac{(.242)(.758)}{120}} \leq \pi_1 \leq .242 + (2.58) \sqrt{\frac{(.242)(.758)}{120}}$$

$$\pi_1 = .242 \pm .101$$

$$.141 \leq \pi_1 \leq .343$$

Thus, the researcher can be 99% confident that the true proportion of cases in the underlying population that falls in **Cell 6/Saturday** is a value between .141 and .343. Stated in probabilistic terms, there is a probability/likelihood of .99 that the true value of the population proportion falls within the range .141 to .343.

The above described procedure can be repeated for the other five cells in Examples 8.1 and 8.2. In each instance the observed frequency of a cell is evaluated in relation to the combined

observed frequencies of the remaining five cells.⁹ Zar (1999, pp. 527–530) describes alternative procedures for computing a confidence interval for a binomially distributed variable.

4. Brief discussion of the z test for a population proportion (Test 9a) and the single-sample test for the median (Test 9b) In Section I it is noted that when $k = 2$ and the value of n is large, the **chi-square goodness-of-fit test** provides a good approximation of the binomial distribution. Under the discussion of the **binomial sign test for a single sample**, two tests are described which yield equivalent results to those obtained with the **chi-square goodness-of-fit test** when $k = 2$. The two tests are the **z test for a population proportion** and the **single-sample test for the median**. In the latter test, the two cells of the chi-square table are comprised of scores that fall above the median of a specific distribution and scores that fall below the median of the distribution. For a full discussion of these tests, the reader should consult the discussion of the **binomial sign test for a single sample**.

5. The correction for continuity for the chi-square goodness-of-fit test Although it is not generally discussed in reference to the **chi-square goodness-of-fit test**, a **correction for continuity** (which is discussed under the **Wilcoxon signed-ranks test (Test 6)**) can be applied to Equation 8.2. The basis for employing the correction for continuity with the **chi-square goodness-of-fit test** is that the test employs a continuous distribution to approximate a discrete distribution (specifically, the binomial or multinomial distributions). The correction for continuity is based on the premise that if a continuous distribution is employed to estimate a discrete distribution, such an approximation will inflate the Type I error rate. By employing the correction for continuity the Type I error rate is ostensibly adjusted to be more compatible with the prespecified alpha value designated by the researcher. Equation 8.6 is the continuity-corrected chi-square equation for the **chi-square goodness-of-fit test**.

$$\chi^2 = \sum_{i=1}^k \left[\frac{(|O_i - E_i| - .5)^2}{E_i} \right] \quad (\text{Equation 8.6})$$

Note that by subtracting .5 from the absolute value of the difference between each set of observed and expected frequencies, the chi-square value derived with Equation 8.6 will be lower than the value computed with Equation 8.2. The magnitude of the correction for continuity will be inversely related to the size of the sample. The correction for continuity for the **chi-square goodness-of-fit test** is only employed when there are $k = 2$ cells. This latter application of the correction is discussed under the **z test for a population proportion**. The use of the correction for continuity with other designs that employ the chi-square statistic is discussed under the **chi-square test for $r \times c$ tables (Test 16)**.

6. Application of the chi-square goodness-of-fit test for assessing goodness-of-fit for a theoretical population distribution In analyzing data there are situations when a researcher may want to determine whether a distribution of sample data conforms to a specific theoretical population (or probability) distribution. As is the case with the **Kolmogorov-Smirnov goodness-of-fit test for a single sample (Test 7)** and the **Lilliefors test for normality (Test 7a)**, the **chi-square goodness-of-fit test** can also be employed for this purpose. Although the **Kolmogorov-Smirnov** and **Lilliefors** tests are designed to be employed with a **continuous** variable and the **chi-square test** is designed to be employed with a **discrete** variable, the latter test is sometimes employed to assess goodness-of-fit for a continuous variable. The most common application of the **chi-square goodness-of-fit test** with a continuous variable is in assessing goodness-of-fit for

a normal distribution, when the population mean and standard deviation have to be estimated from the sample data. Although the **Kolmogorov-Smirnov test** (which stipulates specific values for the population mean and standard deviation) and the **Lilliefors test for normality** (which, like the **chi-square test**, estimates the population mean and standard deviation from the sample data) are better suited for the latter purpose, the **chi-square test** is often used since it requires less computation (which in itself is not sufficient justification for employing a test).

When the **chi-square goodness-of-fit test** is employed to assess goodness-of-fit for a theoretical distribution, Equation 8.3 (i.e., $df = k - 1$) is not appropriate for computing the degrees of freedom. In determining whether a distribution of sample data conforms to a specific theoretical distribution (such as the normal, binomial, or Poisson distributions, all of which will be or have been discussed at some point in the book), it may be necessary to estimate one or more population parameters prior to computing the expected frequency of each cell. In such a case, Equation 8.7 is employed to compute the degrees of freedom for the analysis.

$$df = k - 1 - w \quad \text{(Equation 8.7)}$$

Where: w represents the number of parameters that must be estimated

In actuality, $df = k - 1 - w$ is the generic equation for computing the degrees of freedom for the **chi-square goodness-of-fit test**. Equation 8.3 ($df = k - 1$), which has been used in the examples discussed up to this point, represents the form the equation $df = k - 1 - w$ assumes when $w = 0$.

Example 8.3 will be employed to demonstrate the use of the **chi-square goodness-of-fit test** in assessing goodness-of-fit for a normal distribution. In point of fact, Example 8.3 is almost identical to Example 7.1, which is employed in evaluating the same hypothesis with both the **Kolmogorov-Smirnov goodness-of-fit test for a single sample** and **Lilliefors test for normality**. However, the text of Example 8.3 states that the mean and estimated standard deviation of the population are estimated from the sample data (whereas the latter values are stipulated in Example 7.1). The values $\bar{X} = 90.07$ and $\hat{s} = 34.79$ (which are also employed for the **Lilliefors test**) noted in Example 8.3 were computed by employing Equations I.1 and I.8 with the 30 scores in the sample.

Example 8.3 *A researcher conducts a study to evaluate whether the distribution of the length of time it takes migraine patients to respond to a 100 mg. dose of an intravenously administered drug is normal. The amount of time (in seconds) that elapses between the administration of the drug and cessation of a headache for 30 migraine patients is recorded below. The 30 scores are arranged ordinally (i.e., from fastest response time to slowest response time).*

21, 32, 38, 40, 48, 55, 63, 66, 70, 75, 80, 84, 86, 90, 90, 93, 95, 98, 100, 105, 106, 108, 115, 118, 126, 128, 130, 142, 145, 155

The mean and standard deviation of the population are estimated from the sample data to be $\bar{X} = 90.07$ and $\hat{s} = 34.79$. Do the data conform to a normal distribution?

In order to employ the **chi-square goodness-of-fit test**, the researcher must first estimate the values of the population mean (μ) and standard deviation (σ) by computing the values \bar{X} and \hat{s} from the sample data. Since the latter requires the estimation of two population parameters (i.e., μ and σ), the appropriate degrees of freedom to employ for the analysis will be, $df = k - 1 - 2$. Because the value of k represents the number of cells that are employed in the analysis, there must

be a minimum of four cells. The latter is true, since if k is less than four, the value of df will be less than 1 (which is impossible). Each of the cells in the chi-square table will represent a **class interval**. A class interval is a limited range of values in which scores in a frequency distribution are grouped. As is the case with previous applications of the **chi-square goodness-of-fit test**, the expected frequency for each cell/class interval is computed and contrasted with its observed frequency.

The null and alternative hypotheses that are evaluated with the **chi-square goodness-of-fit test** in reference to Example 8.3 can be stated either in the form presented in Section III, or as follows.

Null hypothesis H_0 : The sample is derived from a normally distributed population.

Alternative hypothesis H_1 : The sample is not derived from a normally distributed population. This is a **nondirectional alternative hypothesis**.

The analysis of Example 8.3 with the **chi-square goodness-of-fit test** is summarized in Tables 8.6 and 8.7.

Table 8.6 Class Intervals for Chi-Square Analysis of Example 8.3

Cell/Class interval/Decile	Limits for z values	Limits for X values
1st decile (0 to .10)	$-1.28 \geq z$	$45.54 \geq X$
2nd decile (> .10 to .20)	$-.84 \geq z > -1.28$	$45.54 < X \leq 60.85$
3rd decile (> .20 to .30)	$-.52 \geq z > -.84$	$60.85 < X \leq 71.98$
4th decile (> .30 to .40)	$-.25 \geq z > -.52$	$71.98 < X \leq 81.37$
5th decile (> .40 to .50)	$0 \geq z > -.25$	$81.37 < X \leq 90.07^*$
6th decile (> .50 to .60)	$.25 \geq z \geq 0$	$90.07 \leq X \leq 98.77^*$
7th decile (> .60 to .70)	$.52 \geq z > .25$	$98.77 < X \leq 108.16$
8th decile (> .70 to .80)	$.84 \geq z > .52$	$108.16 < X \leq 119.29$
9th decile (> .80 to .90)	$1.28 \geq z > .84$	$119.29 < X \leq 134.60$
10th decile (> .90 to 1)	$1.28 < z$	$134.60 < X$

*As a general rule, if two or more scores are equal to the value of \bar{X} , one-half of the scores are assigned to the 5th decile and one-half to the 6th decile. If only one score equals X , it can be randomly assigned to either the 5th or 6th decile.

Table 8.7 Chi-Square Summary Table for Example 8.3

Cell/Class interval/ Decile	O_i	E_i	$(O_i - E_i)$	$(O_i - E_i)^2$	$\frac{(O_i - E_i)^2}{E_i}$
1st decile	4	3	1	1	.33
2nd decile	2	3	-1	1	.33
3rd decile	3	3	0	0	.00
4th decile	2	3	-1	1	.33
5th decile	2	3	-1	1	.33
6th decile	5	3	2	4	1.33
7th decile	4	3	1	1	.33
8th decile	2	3	-1	1	.33
9th decile	3	3	0	0	.00
10th decile	3	3	0	0	.00
	$\Sigma O_i = 30$	$\Sigma E_i = 30$	$\Sigma (O_i - E_i) = 0$	$\chi^2 = 3.31$	

In [Table 8.7](#) each of the $n = 30$ scores has been assigned to one of ten cells/categories. The ten cells, which are summarized in [Table 8.6](#), correspond to the ten **deciles** of the normal distribution. In the **Introduction** it is noted that a **decile** divides a distribution into blocks comprised of ten percentage points (or blocks that comprise a proportion equal to .10 of the distribution). The z scores that correspond to the limits of the ten deciles in a normal distribution were determined through use of [Table A1](#) in the **Appendix**. Thus, the value $z = -1.28$ corresponds to the upper limit of the 10th percentile, since the entry in **Column 3** of [Table A1](#) for $z = -1.28$ is .1033 (which is the closest value to .1000, which is 10% when expressed as a percentage). Given that the value of $\bar{X} = 90.07$ and $\bar{s} = 34.79$, we can compute that the value $X = 45.47$ corresponds to $z = -1.28$ by employing the equation $X = \bar{X} + (z)(\bar{s})$. The latter equation is the algebraic transposition of Equation 1.27 ($z = (X - \mu)/\sigma$), when \bar{X} is employed in place of μ and \bar{s} is employed in place of σ . Thus, if we multiply the value $z = -1.28$ by $\bar{s} = 34.79$ and add $\bar{X} = 90.07$ to the product, we obtain: $X = 90.07 + (-1.28)(34.79) = 45.54$. The latter value indicates that any score less than 45.54 falls in the first decile.

The value $z = -.84$ corresponds to the upper limit of the 20th percentile, since the entry in **Column 3** of [Table A1](#) for $z = -.84$ is .2033 (which is the closest value to .2000, which is 20% when expressed as a percentage). Thus, the second decile will be represented by scores that fall above the proportion .10 (or the 10% point) up to the proportion .20 (or the 20% point). When the value $z = -.84$ is substituted in the equation $X = \bar{X} + (z)(\bar{s})$, we obtain $X = 90.07 + (-.84)(34.79) = 60.85$. The value $X = 60.85$ is the upper limit of the 20th decile. Thus, any score that is greater than 45.54 but equal to or less than 60.85 falls in the 2nd decile. To complete [Table 8.6](#), the procedure that has been described for the 1st and 2nd deciles was employed to determine the limits for the eight remaining deciles.

Employing Equation 8.1, an expected frequency of 3 is computed for each of the cells in [Table 8.7](#) (which is the chi-square summary table) by multiplying the sample size $n = 30$ by .1 (i.e., $E_i = (30)(.1) = 3$). The value .1 is employed to represent π_i in the latter equation, since each cell represents an area that corresponds to 10% of a normal distribution. Thus, the likelihood of an observation falling in any of the cells/deciles is .1.

Employing Equation 8.2, the value $\chi^2 = 3.31$ is computed for Example 8.3. Since there are $k = 10$ cells and $w = 2$ parameters that are estimated, the degrees of freedom for the analysis are $df = 10 - 1 - 2 = 7$. Employing [Table A4](#), we determine that for $df = 7$ the tabled critical .05 and .01 values are $\chi^2_{.05} = 14.07$ and $\chi^2_{.01} = 18.48$. Since the computed value $\chi^2 = 3.31$ is less than both of the aforementioned values, the null hypothesis cannot be rejected. Thus, the analysis does not indicate that the data deviate significantly from a normal distribution. This is consistent with the conclusion that was reached when the same set of data was evaluated with the **Kolmogorov-Smirnov goodness-of-fit test for a single sample** (which employed the population parameters $\mu = 90$ and $\sigma = 35$, which are almost identical to the estimated values $\bar{X} = 90.07$ and $\bar{s} = 34.79$) and the **Lilliefors test for normality** (which, like the **chi-square test**, employed the values $\bar{X} = 90.07$ and $\bar{s} = 34.79$).

It should be noted that because of the small sample size employed in the study, the expected frequency of 3 for all of the cells is less than the minimum value recommended for the **chi-square goodness-of-fit test** by many sources. The values of the expected frequencies could be increased by employing fewer cells in the chi-square table. In other words, one could employ quartile blocks (yielding four cells), or blocks consisting of 20% of the cases per block (yielding five blocks), etc. Daniel (1990) notes that the outcome of the **chi-square goodness-of-fit test** is affected by the number of cells that are employed in the analysis, and cites studies (e.g., Dahiya and Gurland (1973)) that address this issue. Further discussion of the application of the **chi-square goodness-of-fit test** with a continuous variable can be found in Conover (1980, 1999), Daniel (1990), and Siegel and Castellan (1988). Conover (1980, 1999) and Daniel (1990)

describe the test protocol when the format of data is a frequency distribution that reflects the number of scores in each of k class intervals. The latter format is most likely to be employed if there are a large number of scores, and the researcher elects to group scores in class intervals (such as 20 scores falling within the range 1–10, 15 scores falling within the range 11–20, etc.), since it provides a succinct way of summarizing the data. In other instances where the original data are grouped in class intervals, a researcher may not have access to the exact value of each score, but have only a frequency distribution that categorizes each score within one of k class intervals.

7. Sources for computing the power of the chi-square goodness-of-fit test Cohen (1977, 1988) has developed a statistic called the **w index** that can be employed to compute the power of the **chi-square goodness-of-fit test**. The value w is an **effect size** index reflecting the difference between expected and observed frequencies. The concept of effect size is discussed in Section VI of the **single-sample t test (Test 2)**. It is discussed in greater detail in Section VI of the **t test for two independent samples (Test 11)**, and in Section IX (the **Addendum**) of the **Pearson product-moment correlation coefficient (Test 28)** under the discussion of **meta-analysis and related topics**.

The equation for the **w index** is $w = \sqrt{\Sigma[(P_{alt} - P_{null})^2/P_{null}]}$. The latter equation indicates the following: a) For each of the cells in the chi-square table, the proportion of cases hypothesized in the null hypothesis is subtracted from the proportion of cases hypothesized in the alternative hypothesis; b) The obtained difference in each cell is squared, and then divided by the proportion hypothesized in the null hypothesis for that cell; c) All of the values obtained for the cells in part b) are summed; and d) w represents the square root of the sum obtained in part c).

Cohen (1977; 1988, Ch. 7) has derived tables that allow a researcher to determine, through use of the **w index**, the appropriate sample size to employ if one wants to test a hypothesis about the difference between observed and expected frequencies in a chi-square table at a specified level of power. Cohen (1977; 1988, pp. 224–226) has proposed the following (admittedly arbitrary) w values as criteria for identifying the magnitude of an effect size: a) A **small effect size** is one that is greater than .1 but not more than .3; b) A **medium effect size** is one that is greater than .3 but not more than .5; and c) A **large effect size** is greater than .5.

8. Heterogeneity chi-square analysis Assume that a researcher conducts m independent studies (where $m \geq 2$) which evaluate the same goodness-of-fit hypothesis, and that none of the studies yields a statistically significant result. However, visual inspection of the data suggests a consistent pattern of differences for the observed frequencies of the k categories employed in each of the m studies. The researcher suspects that because of the relatively small sample sizes employed in the studies, the absence of significant results is largely due to a lack of statistical power. In order to increase the power of the analysis, the researcher wants to combine the data for the m studies into one table, and evaluate the latter table with the **chi-square goodness-of-fit test**. Zar (1999, pp. 471–473) notes that the procedure for determining whether or not a researcher is justified in pooling data under such conditions is referred to as **heterogeneity chi-square analysis** (also referred to as **interaction chi-square analysis** or **homogeneity chi-square analysis**).

The null and alternative hypotheses that are evaluated with a **heterogeneity chi-square analysis** are as follows.

Null hypothesis H_0 : The m samples are derived from the same population (i.e., population homogeneity).

Alternative hypothesis H_1 : At least two of the m samples are not derived from the same population (population heterogeneity).

Example 8.4 will be employed to illustrate the **heterogeneity chi-square analysis**.

Example 8.4 *A researcher evaluates a hypothesis that in the lakes of a specific geographical region the number of fish representing three different species are equally distributed. Over a period of a year four separate studies are conducted, and each study is evaluated with a **chi-square goodness-of-fit test**. Although none of the studies yields a significant result (which if present would allow the researcher to conclude that the species of fish are not equally distributed), visual inspection of the data suggests that **Species 3** is more prevalent than either **Species 1** or **2**, and that of the three species, **Species 1** is the least prevalent. Because he suspects that the nonsignificant results for the chi-square analyses may be due to a lack of statistical power, the researcher would like to combine the data for the four studies, and analyze the pooled data. Is the researcher justified in pooling the data?*

Table 8.8 summarizes the analysis of the data for Example 8.4. **Part A** of **Table 8.8** presents the chi-square goodness-of-fit analysis for each of the four individual studies. Column 2 for each of the studies contains the observed species frequency for that study. In each study the expected frequency for any of the $k = 3$ cells is one-third of the total number of observations (i.e., $E_i = (n)(1/3)$, since the latter implies that the species are equally distributed).

The following protocol is employed in the **heterogeneity chi-square analysis**: a) A chi-square value is computed for each of the individual studies. (Although it is not the case in our example, Zar (1999) notes that if the number of cells per study is $k = 2$, the correction for continuity is not used in analyzing the individual tables.); b) The sum of the m chi-square values obtained in a) for the individual studies is computed. The latter value itself represents a chi-square value, and will be designated χ_{sum}^2 . In addition, the sum of the degrees of freedom for the m studies is computed. The latter degrees of freedom value, which will be designated df_{sum} , is obtained by summing the value $df = k - 1$ m times; c) The data for the m studies is combined into one table, and the chi-square value, which will be designated χ_{pooled}^2 , is computed for the pooled data. The degrees of freedom for the table with the pooled data, which will be designated df_{pooled} , is equal to $df = k - 1$. (Zar (1999) notes that if there are $k = 2$ cells, the correction for continuity is not used in analyzing the table with the pooled data); d) The **heterogeneity chi-square analysis** is based on the premise that if the m samples are in fact homogeneous, the sum of the m individual chi-square values (χ_{sum}^2) should be approximately the same value as the chi-square value computed for the pooled data (χ_{pooled}^2). In order to determine the latter, the absolute value of the difference between the sum of the m chi-square values (obtained in b)) and the pooled chi-square value (obtained in c)) is computed. The obtained difference, which is itself a chi-square value, is the **heterogeneity chi-square value**, which will be designated χ_{het}^2 . Thus, $\chi_{het}^2 = |\chi_{sum}^2 - \chi_{pooled}^2|$. The null hypothesis will be rejected when there is a large difference between the values of χ_{sum}^2 and χ_{pooled}^2 . The value χ_{het}^2 , which represents the test statistic, is evaluated with a degrees of freedom value that is the sum of the degrees of freedom for the m individual studies (df_{sum}) less the degrees of freedom obtained for the table with the pooled data (df_{pooled}). Thus, $df_{het} = df_{sum} - df_{pooled}$. In order to reject the null hypothesis, the value χ_{het}^2 must be equal to or greater than the tabled critical value at the prespecified level of significance for df_{het} ; and e) If the null hypothesis is rejected the data cannot be pooled. If, however, the null hypothesis is retained, the data can be pooled, and the computed value for χ_{pooled}^2 is employed to evaluate the goodness-of fit hypothesis. Zar (1999) notes, however, that if there are $k = 2$ cells

Table 8.8 Heterogeneity Chi-Square Analysis for Example 8.4

A. Chi-square analysis of four individual studies					
Study 1					
Cell/Species	O_i	E_i	$(O_i - E_i)$	$(O_i - E_i)^2$	$\frac{(O_i - E_i)^2}{E_i}$
1	10	15	-5	25	1.67
2	15	15	0	0	0
3	20	15	5	25	1.67
$\Sigma O_i = 45$		$\Sigma E_i = 45$	$\Sigma(O_i - E_i) = 0$		$\chi_1^2 = 3.33$
Study 2					
Cell/Species	O_i	E_i	$(O_i - E_i)$	$(O_i - E_i)^2$	$\frac{(O_i - E_i)^2}{E_i}$
1	13	20	-7	49	2.45
2	21	20	1	1	.05
3	26	20	6	36	1.80
$\Sigma O_i = 60$		$\Sigma E_i = 60$	$\Sigma(O_i - E_i) = 0$		$\chi_2^2 = 4.30$
Study 3					
Cell/Species	O_i	E_i	$(O_i - E_i)$	$(O_i - E_i)^2$	$\frac{(O_i - E_i)^2}{E_i}$
1	19	25	-6	36	1.44
2	22	25	-3	9	.36
3	34	25	9	81	3.24
$\Sigma O_i = 75$		$\Sigma E_i = 75$	$\Sigma(O_i - E_i) = 0$		$\chi_3^2 = 5.04$
Study 4					
Cell/Species	O_i	E_i	$(O_i - E_i)$	$(O_i - E_i)^2$	$\frac{(O_i - E_i)^2}{E_i}$
1	12	20	-8	65	3.20
2	22	20	2	4	.20
3	26	20	6	36	1.80
$\Sigma O_i = 60$		$\Sigma E_i = 60$	$\Sigma(O_i - E_i) = 0$		$\chi_4^2 = 5.20$
Sum of chi-square values for four studies = $\chi_{sum}^2 = 3.33 + 4.30 + 5.04 + 5.20 = 17.87$					
B. Chi-square analysis of pooled data					
Pooled data for $m = 4$ studies					
Cell/Species	O_i	E_i	$(O_i - E_i)$	$(O_i - E_i)^2$	$\frac{(O_i - E_i)^2}{E_i}$
1	54	80	-26	676	8.45
2	80	80	0	0	0
3	106	80	26	676	8.45
$\Sigma O_i = 240$		$\Sigma E_i = 240$	$\Sigma(O_i - E_i) = 0$		$\chi_{pooled}^2 = 16.90$
C. Heterogeneity of chi-square analysis					
Heterogeneity chi-square = Sum of chi-square values for four studies – Pooled chi-square value					
$\chi_{het}^2 = (\chi_{sum}^2 = 17.87) - (\chi_{pooled}^2 = 16.90) = .97$					

(i.e., $df = 1$), the table for the pooled data should be reevaluated employing the correction for continuity, and the continuity-corrected χ^2_{pooled} value (which will be a little lower than the original χ^2_{pooled} value) should be employed to evaluate the goodness-of-fit hypothesis.

The computed chi-square values for the four studies in Table 8.8 are $\chi^2_1 = 3.33$, $\chi^2_2 = 4.30$, $\chi^2_3 = 5.04$, and $\chi^2_4 = 5.20$. Since, in each of the four chi-square tables, there are $k = 3$ cells, $df = k - 1 = 2$ for each table. Thus, the total number of degrees of freedom employed for the four studies is $df_{sum} = (4)(2) = 8$ (i.e., the number of studies (4) multiplied by the number of degrees of freedom per study (2)). Since there are $k = 3$ cells in the table for the pooled data, the degrees of freedom for the latter table is $df_{pooled} = k - 1 = 2$. By summing the chi-square values for the four studies, we compute the value $\chi^2_{sum} = 3.33 + 4.30 + 5.04 + 5.20 = 17.87$. Since, in Part B of Table 8.8, we compute $\chi^2_{pooled} = 16.90$, the value for heterogeneity chi-square (computed in Part C of Table 8.8) is $\chi^2_{het} = |(\chi^2_{sum} = 17.87) - (\chi^2_{pooled} = 16.90)| = .97$. The degrees of freedom employed to evaluate the latter chi-square value are $df_{het} = (df_{sum} = 8) - (df_{pooled} = 2) = 6$. The tabled critical .05 and .01 chi-square values in Table A4 for $df = 6$ are $\chi^2_{.05} = 12.59$ and $\chi^2_{.01} = 16.81$. Since the computed value $\chi^2_{het} = .97$ is less than $\chi^2_{.05} = 12.59$, the null hypothesis is retained. In other words we can conclude the four samples are homogeneous (i.e., come from the same population), and thus we can justify pooling the data into a single table.

As noted earlier, in Part B of Table 8.8 the value $\chi^2 = 16.90$ is computed for the pooled data. Since there are $k = 3$ cells in the chi-square table for the pooled data, $df = k - 1 = 2$. The tabled critical .05 and .01 values in Table A4 for $df = 2$ are $\chi^2_{.05} = 5.99$ and $\chi^2_{.01} = 9.21$. Since the value $\chi^2_{pooled} = 16.90$ is larger than both of the aforementioned critical values, the goodness-of-fit null hypothesis for the pooled data can be rejected at both the .05 and .01 levels. In other words, with respect to the pooled data, we can conclude that in the case of at least one of the cells/species there is a difference between its observed and expected frequency. Without conducting additional comparisons, it appears that, as the researcher suspected, the observed frequency for Cell/Species 1 is significantly below its expected frequency, while the observed frequency for Cell/Species 3 is significantly above its expected frequency. Although it does not apply to our example, as noted earlier, Zar (1999) (who provides a comprehensive discussion of the **heterogeneity chi-square analysis**) states that if the number of cells in the table for the pooled data is $k = 2$, the latter table should be reevaluated employing the correction for continuity.

It should be emphasized that a researcher should employ common sense in applying the heterogeneity chi-square analysis described in this section. To be more specific, there may be occasions when even though the computed value of χ^2_{het} is not significant, in spite of the latter it would not be recommended that the researcher pool the data from two or more smaller tables. To be more specific, one should not pool data from two or more tables employing small sample sizes (which when evaluated individually fail to yield a significant chi-square value) in order to obtain a significant pooled chi-square value, when there is an obvious inconsistency in the cell proportions for two or more of the tables. In other words, when the data from m tables are pooled, the proportion of cases in the cells of each of the m tables should be approximately the same. Everitt (1977, 1992) and Fleiss (1981) recommend alternative procedures for pooling the data from multiple chi-square tables.

VII. Additional Discussion of the Chi-Square Goodness-of-Fit Test

1. Directionality of the chi-square goodness-of-fit test In Section III it is noted that most sources state the alternative hypothesis for the **chi-square goodness-of-fit test** nondirectionally, but that in actuality it is possible to state the alternative hypothesis directionally. This is most obvious when there are $k = 2$ cells and the expected probability associated with each cell is

$\pi_i = 1/2$. Under the latter conditions a researcher can make two directional predictions, either one of which can represent the alternative hypothesis. Specifically, the following can be predicted with respect to the sample data: a) The observed frequency of Cell 1 will be significantly higher than the observed frequency of Cell 2 (which translates into the observed frequency of Cell 1 being higher than its expected frequency, and the observed frequency of Cell 2 being lower than its expected frequency); and b) The observed frequency of Cell 2 will be significantly higher than the observed frequency of Cell 1 (which translates into the observed frequency of Cell 2 being higher than its expected frequency, and the observed frequency of Cell 1 being lower than its expected frequency).

If a researcher wants to evaluate either of the aforementioned directional alternative hypotheses at the .05 level, the appropriate critical value to employ is the tabled chi-square value (for $df = 1$) at the .10 level of significance. The latter value is represented by the tabled chi-square value at the 90th percentile (which demarcates the extreme 10% in the right tail of the chi-square distribution). This latter critical value will be designated as $\chi^2_{.10}$ throughout this discussion. The rationale for employing $\chi^2_{.10}$ in evaluating the directional alternative hypothesis at the .05 level is as follows. When $k = 2$ and the alternative hypothesis is stated nondirectionally, if a computed chi-square value is equal to or greater than $\chi^2_{.05}$ (for $df = 1$), the researcher can reject the null hypothesis if the data are consistent with either of the outcomes associated with the two possible directional alternative hypotheses. If that same tabled critical chi-square value is employed to evaluate one of the two possible directional alternative hypotheses, a directional alternative hypothesis would be evaluated not at the .05 level but at one-half that value — in other words at the .025 level. Thus, if one wants to employ $\alpha = .05$ and states the alternative hypothesis directionally, the alpha level for the directional alternative hypothesis should be .05 multiplied by the number of possible directional alternative hypotheses (which in this instance equals 2). By employing the tabled critical value for $\chi^2_{.10}$, which is a lower value than $\chi^2_{.05}$, an alpha level (and Type I error rate) of .05 is established for the specific one-tailed alternative hypothesis that one employs. The area of the chi-square distribution that corresponds to the alpha level for the latter directional alternative hypothesis will be one-half of the area that comprises the extreme 10% of the right tail of the distribution. The area that corresponds to the alpha level for the other directional alternative hypothesis will be the remaining 5% of the extreme 10% in the right tail of the distribution.

If we turn our attention to Examples 8.1 and 8.2, in both examples there are, in fact, 720 possible directional predictions the researcher can make!¹⁰ The latter value is determined as follows: $k! = 6! = (6)(5)(4)(3)(2)(1) = 720$.¹¹ In other words, a researcher can predict any one of 720 ordinal configurations with respect to the observed frequencies of the six cells. As an example, the researcher might predict that **1/Monday** will have the highest observed frequency, followed in order by **2/Tuesday**, **3/Wednesday**, **4/Thursday**, **5/Friday**, and **6/Saturday**, and only be willing to reject the null hypothesis if the data are consistent with this specific ordering of the observed cell frequencies.

Later in this section it will be explained that when $k = 6$, it is not possible to evaluate any one of the 720 directional alternative hypotheses at either the .05 or .01 level of significance. Indeed, under these conditions the highest value of alpha that can be employed to evaluate a directional alternative hypothesis is approximately .001. In point of fact, when $k = 6$, the tabled critical $\chi^2_{.001}$ value is approximately 2.7, which happens to be the tabled chi-square value at the 28th percentile. This is the case, since if the prespecified alpha value that is employed to evaluate a nondirectional alternative hypothesis (which in this case we will assume is .001, since it is the highest value that will work with $k = 6$) is multiplied by the number of possible directional alternative hypotheses (720) we obtain: $(.001)(720) = .72$. The value .72 demarcates the extreme 72% in the right tail of the chi-square distribution when $df = 5$. Thus, it corresponds to the 28th

percentile of the distribution, since $(1 - .72) = .28$. Consequently, in order to reject the null hypothesis with reference to one of the 720 possible directional alternative hypotheses, both of the following conditions will have to be met: a) The obtained value of chi-square will have to be equal to or greater than the tabled chi-square value at the 28th percentile; and b) The data will have to be consistent with the directional alternative hypothesis that is employed. In other words, the ordinal relationship between the observed frequencies of the six cells should be in the exact order stated in the directional alternative hypothesis.

As noted previously, none of the 720 possible directional alternative hypotheses can be evaluated at either the .05 or .01 levels. This is the case since, if either .05 or .01 is multiplied by 720, the resulting product exceeds unity (1) — i.e., $(.05)(720) = 36$ and $(.01)(720) = 7.2$. Since both 36 and 7.2 exceed 1, they cannot be used as probability values. Thus, it is impossible to evaluate any of the directional alternative hypotheses at either the .05 or .01 level. In fact, the largest alpha level at which any of the directional alternative hypotheses can be evaluated is .001388, since $1/720 = .001388$ (i.e., the value .001388 is the maximum number which when multiplied by 720 falls short of 1. Specifically, $(.001388)(720) = .99936$).

On initial inspection it might appear that by employing $\chi^2_{.72}$ to evaluate one of the directional alternative hypotheses, a researcher is employing an inflated alpha level.¹² But as just noted, in this instance the alpha level for a directional alternative hypothesis is, in fact, .001. Of course a researcher may elect to employ a larger critical chi-square value, and if one elects to do so, the actual alpha level for a directional alternative hypothesis will be even lower than .001. For example, if the tabled critical value $\chi^2_{.05} = 11.07$ (which is the tabled value for $df = 5$ at the 95th percentile that is employed in evaluating a nondirectional alternative hypothesis) is employed to evaluate one of the 720 possible directional alternative hypotheses, the actual alpha level that one will be using in evaluating the directional alternative hypothesis will be $.05/720 = .00007$. In such a case there is obviously a minuscule likelihood of committing a Type I error in reference to the directional alternative hypothesis. Yet at the same time, the power of the analysis with respect to that alternative hypothesis will be minimal (thus resulting in a high likelihood of committing a Type II error).

It is also possible in Examples 8.1 and 8.2 to state an alternative hypothesis that predicts two or more, but less than 720, of the possible ordinal configurations with respect to the observed frequencies of the $k = 6$ cells. In other words, a directional alternative hypothesis might state that the null hypothesis can only be rejected if the magnitude of the observed cell frequencies in descending order is either **Cell 1, Cell 2, Cell 3, Cell 4, Cell 5, Cell 6** or **Cell 2, Cell 1, Cell 3, Cell 4, Cell 5, Cell 6**. In such a case, to evaluate the null hypothesis at the .001 level with respect to an alternative hypothesis involving two of the 720 possible ordinal configurations, the tabled critical chi-square value at the 64th percentile is employed (i.e., $\chi^2_{.36}$ since the area of the distribution involved is the extreme 36% $((1 - .64) = .36)$ that falls in the right tail). The general procedure for computing the percentile rank in the chi-square distribution in determining the critical value when evaluating one or more configurations is as follows: a) Divide the total number of possible configurations by the number of acceptable configurations stated in the directional alternative hypothesis; b) Multiply the result of the division by the prespecified alpha level; and c) Subtract the value obtained in part b) from 1.

Applying this protocol to a directional alternative hypothesis in which only 2 out of 720 configurations are acceptable, we derive: a) $720/2 = 360$; b) $(360)(.001) = .36$; and c) $(1 - .36) = .64$. The resulting value of .64 (which can be converted to 64%) corresponds to the percentile rank in the chi-square distribution to employ in determining the critical value. The value .36 obtained in part b) represents the overall proportion of the right tail of the distribution which contains a proportion of the distribution equivalent to .001 that represents the rejection zone for the directional alternative hypothesis under study.

It should be noted that since $2/720 = .0028$, an alternative hypothesis involving 2 out of 720 possible configurations can be evaluated at a level above .001. In point of fact, such an alternative hypothesis can be evaluated at any level equal to or less than .0028. Thus if one elects to employ $\alpha = .002$, using the protocol described in the previous paragraph, $(720/2)(.002) = .72$, and $(1 - .72) = .28$. The latter result indicates that $\chi^2_{.72} = 2.7$ is once again employed as the critical value. This is the case, since the latter value represents the tabled value at 28th percentile for $df = 5$.

In closing this discussion, the reader should take note of the fact that all of the critical values for the **chi-square goodness-of-fit test** are derived from the right tail of the chi-square distribution. In point of fact, with the exception of the **single-sample chi-square test for a population variance** (in which case critical values are derived from both tails of the distribution), all of the tests in the book that employ the chi-square distribution only use critical values from the right tail of the distribution.

2. Additional goodness-of-fit tests In addition to the **chi-square goodness-of-fit test**, the **Kolmogorov–Smirnov goodness-of-fit test for a single sample**, and **Lilliefors test for normality** (both of which have been alluded to in this chapter),¹³ there are a number of other tests that have been developed for evaluating goodness-of-fit. Three other tests discussed in the book that can be employed to assess goodness-of-fit for a normal distribution are the **single sample test for evaluating population skewness (Test 4)**, the **single sample test for evaluating population kurtosis (Test 5)**, and the **D’Agostino–Pearson test of normality (Test 5a)**. Most of the alternative goodness-of-fit tests (including the **Kolmogorov–Smirnov** and **Lilliefors tests**) evaluate scores that are assigned to ordered categories.¹⁴ Among the other goodness-of-fit tests that have been developed for evaluating ordered categorical data are **David’s empty cell test** (David (1950)), the **Cramér–von Mises goodness-of-fit test** (attributed to Cramér (1928), von Mises (1931), and Smirnov (1936)), and the **Shapiro–Wilk test for normality** (Shapiro and Wilk (1965, 1968)) (which is described in Conover (1980, 1999)). D’Agostino and Stephens (1996) and Daniel (1990) contain comprehensive discussions of alternative goodness-of-fit procedures.

The general subject of goodness-of-fit tests for randomness is discussed in Section VII of the **single-sample runs tests (Test 10)**. **Autocorrelation**, a procedure that can also be employed for assessing goodness-of-fit for randomness, is discussed in Section VII of the **Pearson product–moment correlation coefficient**.

VIII. Additional Examples Illustrating the Use of the Chi-Square Goodness-of-Fit Test

Three additional examples that can be evaluated with the **chi-square goodness-of-fit test** are presented in this section. Example 8.5 employs the same data set as Examples 8.1 and 8.2, and thus yields the same results. Examples 8.6 and 8.7 illustrate the application of the **chi-square goodness-of-fit test** to data in which the expected frequencies are based on existing empirical information or theoretical conjecture rather than on expected/theoretical probabilities.

Example 8.5 *The owner of the Big Wheel Speedway, a stock car racetrack, asks a researcher to determine whether or not there is any bias associated with the lane to which a car is assigned at the beginning of a race. Specifically, the owner wishes to determine if there is an equal likelihood of winning a race associated with each of the six lanes of the track. The researcher examines the results of 120 races and determines the following number of first place finishes for the six lanes: Lane 1 – 20; Lane 2 – 14; Lane 3 – 18; Lane 4 – 17; Lane 5 – 22; Lane 6 – 29.*

Example 8.6 A country in which four ethnic groups make up the population establishes affirmative action guidelines for medical school admissions. The country has one medical school, and it is mandated that each new class of medical students proportionally represents the four ethnic groups that comprise the country's population. The four ethnic groups that make up the population and the proportion of people in each ethnic group are: *Balzacs* (.4), *Crosacs* (.25), *Murads* (.3), and *Isads* (.05).¹⁵ The number of students from each ethnic group admitted into the medical school class for the new year are: *Balzacs* (300), *Crosacs* (220), *Murads* (400), and *Isads* (80). Is there a significant discrepancy between the proportions mandated in the affirmative action guidelines and the actual proportion of the four ethnic groups in the new medical school class?

Except for the fact that empirical data are used as a basis for determining the expected cell frequencies, this example is evaluated in the same manner as Examples 8.1 and 8.2. There are $k = 4$ cells — each cell representing one of the four mutually exclusive ethnic groups. The observed frequencies are the number of students from each of the four ethnic groups out of the total of 1000 students who are admitted to the medical school (i.e., $n = 300 + 220 + 400 + 80 = 1000$). The expected frequencies are computed based upon the proportion of each ethnic group in the population. Each of these values is obtained by multiplying the total number of medical school admissions (1000) by the proportion of a specific ethnic group in the population. Thus in the case of the **Balzacs**, employing Equation 8.1 the expected frequency is computed as follows: $E_1 = (1000)(.4) = 400$. In the same respect, the expected frequencies for the other three ethnic groups are: **Crosacs**: $E_2 = (1000)(.25) = 250$; **Murads**: $E_3 = (1000)(.3) = 300$; and **Isads**: $E_4 = (1000)(.05) = 50$. Table 8.9 summarizes the observed and expected frequencies and the resulting values employed in the computation of the chi-square value through use of Equation 8.2.

Table 8.9 Chi-Square Summary Table for Example 8.6

Cell	O_i	E_i	$(O_i - E_i)$	$(O_i - E_i)^2$	$\frac{(O_i - E_i)^2}{E_i}$
Balzacs	300	400	-100	10000	25
Crosacs	220	250	-30	900	3.6
Murads	400	300	100	10000	33.3
Isads	80	50	30	900	18
$\Sigma O_i = 1000$		$\Sigma E_i = 1000$	$\Sigma(O_i - E_i) = 0$		$\chi^2 = 79.9$

Employing Table A4, we determine that for $df = 4 - 1 = 3$ the tabled critical .05 and .01 values are $\chi^2_{.05} = 7.81$ and $\chi^2_{.01} = 11.34$. (A nondirectional alternative hypothesis is assumed.) Since the computed value $\chi^2 = 79.9$ is greater than both of the aforementioned critical values, the null hypothesis can be rejected at both the .05 or .01 levels. Based on the chi-square analysis it can be concluded that the medical school admissions data do not adhere to the proportions mandated in the affirmative action guidelines. Inspection of Table 8.9 suggests that the significant difference is primarily due to the presence of too many **Murads** and **Isads** and too few **Balzacs**. This observation can be confirmed by employing the appropriate comparison procedure described in Section VI.

Example 8.7 A physician who specializes in genetic diseases develops a theory which predicts that two-thirds of the people who develop a disease called cyclomeiosis will be males. She randomly selects 300 people who are afflicted with cyclomeiosis and observes that 140 of them are females. Is the physician's theory supported?

In Example 8.7 there are two cells, each representing one gender. Since the expected frequencies are computed on the basis of the probabilities hypothesized in the physician's theory, two-thirds of the sample are expected to be males and the remaining one-third females. Thus, the respective expected frequencies for males and females are determined as follows: **Males:** $E_1 = (300)(2/3) = 200$; **Females:** $E_2 = (300)(1/3) = 100$. Since 140 females are observed with the disease, the remaining 160 people who have the disease must be males. [Table 8.10](#) summarizes the observed and expected frequencies and the resulting values that are employed in the computation of the chi-square value with Equation 8.2.

Table 8.10 Chi-Square Summary Table for Example 8.7

Cell	O_i	E_i	$(O_i - E_i)$	$(O_i - E_i)^2$	$\frac{(O_i - E_i)^2}{E_i}$
Males	160	200	-40	1600	8
Females	140	100	40	1600	16
	$\Sigma O_i = 300$	$\Sigma E_i = 300$	$\Sigma(O_i - E_i) = 0$		$\chi^2 = 24$

Employing [Table A4](#), we determine that for $df = 2 - 1 = 1$ the tabled critical .05 and .01 values are $\chi^2_{.05} = 3.84$ and $\chi^2_{.01} = 6.63$.¹⁶ Since the computed value $\chi^2 = 24$ is greater than both of the aforementioned critical values, the null hypothesis can be rejected at both the .05 or .01 levels. Based on the chi-square analysis, it can be concluded that the observed distribution of males and females for the disease is not consistent with the doctor's theory.

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Endnotes

1. Categories are **mutually exclusive** if assignment to one of the k categories precludes a subject/object from being assigned to any one of the remaining $(k - 1)$ categories.
2. The reason why the exact probabilities associated with the binomial and multinomial distributions are generally not computed is because, except when the value of n is very small, an excessive amount of computation is involved. The **binomial distribution** is discussed under the **binomial sign test for a single sample**, and the **multinomial distribution** is discussed in Section IX (the **Addendum**) of the latter test.
3. Example 8.5 in Section VIII illustrates an example in which the expected frequencies are based on prior empirical information.
4. It is possible for the value of the numerator of a probability ratio to be some value other than 1. For instance, if one is evaluating the number of odd versus even numbers that appear on n rolls of a die, in each trial there are $k = 2$ categories. Three face values (1, 3, 5) will result in an observation being categorized as an odd number, and three face values (2, 4, 6) will result in an observation being categorized as an even number. Thus, the probability associated with each of the two categories will be $3/6 = 1/2$. It is also possible for each of the categories to have different probabilities. Thus, if one is evaluating the relative occurrence of the face values 1 and 2 versus the face values 3, 4, 5, and 6, the probability associated

with the former category will be $2/6 = 1/3$ (since two outcomes fall within the category 1/2), while the probability associated with the latter will be $4/6 = 2/3$ (since four outcomes fall within the category 3/4/5/6). Examples 8.6 and 8.7 in Section VIII illustrate examples where the probabilities for two or more categories are not equal to one another.

5. When decimal values are involved, there may be a minimal difference between the sums of the expected and observed frequencies due to rounding off error.
6. There are some instances when Equation 8.3 should be modified to compute the degrees of freedom for the **chi-square goodness-of-fit test**. The modified degrees of freedom equation is discussed in Section VI, within the framework of employing the **chi-square goodness-of-fit test** to assess goodness-of-fit for a normal distribution.
7. Sometimes when one or more cells in a set of data have an expected frequency of less than five, by combining cells (as is done in this analysis) a researcher can reconfigure the data so that the expected frequency of all the resulting cells is greater than five. Although this is one way of dealing with the violation of the assumption concerning the minimum acceptable value for an expected cell frequency, the null hypothesis evaluated with the reconfigured data will not be identical to the null hypothesis stipulated in Section III.
8. In a one-dimensional chi-square table, subjects/objects are assigned to categories which reflect their status on a single variable. In a two-dimensional table, two variables are involved in the categorization of subjects/objects. As an example, if each of n subjects is assigned to a category based on one's gender and whether one is married or single, a two-dimensional table can be constructed involving the following four cells: **Male-Married; Female-Married; Male-Not married; Female-Not married**. Note that people assigned to a given cell fall into one of the two categories on each of the two dimensions/variables (which are gender and marital status). Analysis of two-dimensional tables is discussed under the **chi-square test for $r \times c$ tables**. In Section VII of the latter test, tables with more than two dimensions (commonly referred to as **multidimensional contingency tables**) are also discussed.
9. Daniel (1990) notes that the procedure described in this section will only yield reliable results when $n\pi_1$ and $n(1 - \pi_1)$ are both greater than 5. It is assumed that the researcher estimates the value of π_1 prior to collecting the data. The researcher bases the latter value either on probability theory or preexisting empirical information. Generally speaking, if the value of n is large, the value of p_1 should provide a reasonable approximation of the value of π_1 for calculating the values $n\pi_1$ and $n(1 - \pi_1)$.
10. Since, when $k = 2$, it is possible to state two directional alternative hypotheses, some sources refer to an analysis of such a nondirectional alternative hypothesis as a two-tailed test. Using the same logic, when $k > 2$ one can conceptualize a test of a nondirectional alternative hypothesis as a **multi-tailed test** (since, when $k > 2$, it is possible to have more than two directional alternative hypotheses). It should be pointed out that since the **chi-square goodness-of-fit test** only utilizes the right tail of the distribution, it is questionable to use the terms two-tailed or multi-tailed in reference to the analysis of a nondirectional alternative hypothesis.

11. $k!$ is referred to as **k factorial**. The notation indicates that the integer number preceding the

$n!$ is multiplied by all integer values below it. Thus, $k! = (k)(k-1) \dots (1)$. By definition $0!$ is set equal to 1. A method of computing an approximate value for $n!$ was developed by James Stirling (1730). (The letter n is more commonly employed as the notation to represent the number for which a factorial value is computed.) **Stirling's approximation** (described in Feller (1968), Miller and Miller (1999) and Zar (1999)) is $n! = \sqrt{2n\pi} (n/e)^n$ which can also be written as $n! = \sqrt{2\pi} (n^{n+0.5})(e^{-n})$. As noted in Endnote 5 in the **Introduction**, the value e in the Stirling equation is the base of the natural system of logarithms. e , which equals 2.71828..., is an **irrational number** (i.e., a number that has a decimal notation that goes on forever without a repeating pattern of digits).

12. The subscript .72 in the notation $\chi^2_{.72}$ represents the .72 level of significance. The value .72 is based on the fact that the extreme 72% of the right tail of the chi-square distribution is employed in evaluating the directional alternative hypothesis. The value $\chi^2_{.72}$ falls at the 28th percentile of the distribution.
13. The two most commonly employed (as well as discussed) goodness-of-fit tests are the **chi-square goodness-of-fit test** and the **Kolmogorov-Smirnov goodness-of-fit test for a single sample**. A general discussion of differences between the latter two tests can be found in Section VII of the **Kolmogorov-Smirnov goodness-of-fit test for a single sample**.
14. When categories are ordered, there is a direct (or inverse) relationship between the magnitude of the score of a subject on the variable being measured and the ordinal position of the category to which that score has been assigned. An example of ordered categories which can be employed with the **chi-square goodness-of-fit test** are the following four categories that can be used to indicate the magnitude of a person's IQ: **Cell 1 – 1st quartile; Cell 2 – 2nd quartile; Cell 3 – 3rd quartile; and Cell 4 – 4th quartile**. The aforementioned categories can be employed if one wants to determine whether, within a sample, an equal number of subjects are observed in each of the four quartiles. Note that in Examples 8.1 and 8.2, the fact that an observation is assigned to Cell 6 is not indicative of a higher level of performance or superior quality than an observation assigned to Cell 1 (or vice versa). However, in the IQ example, there is a direct relationship between the number used to identify each cell and the magnitude of IQ scores for subjects who have been assigned to that cell.
15. Note that the sum of the proportions must equal 1.
16. Even though a nondirectional alternative hypothesis will be assumed, this example illustrates a case in which some researchers might view it more prudent to employ a directional alternative hypothesis.

Test 9

The Binomial Sign Test for a Single Sample (Nonparametric Test Employed with Categorical/Nominal Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test In an underlying population comprised of two categories that is represented by a sample, is the proportion of observations in one of the two categories equal to a specific value?

Relevant background information on test The **binomial sign test for a single sample** is based on the **binomial distribution**, which is one of a number of **discrete probability distributions** discussed in this chapter. A **discrete probability distribution** is a distribution in which the values a variable may assume are finite (as opposed to a **continuous probability distribution** in which a variable may assume an infinite number of values). The basic assumption underlying the binomial distribution is that each of n independent observations (i.e., the outcome for any given observation is not influenced by the outcome for any other observation) is randomly selected from a population, and that each observation can be classified in one of $k = 2$ mutually exclusive categories. Within a binomially distributed population, the likelihood that an observation will fall in Category 1 will equal π_1 , and the likelihood that an observation will fall in Category 2 will equal π_2 . Since it is required that $\pi_1 + \pi_2 = 1$, it follows that $\pi_2 = 1 - \pi_1$.¹ The mean (μ , which is also referred to as the **expected value**) and standard deviation (σ) of a binomially distributed variable are computed with Equations 9.1 and 9.2.²

$$\mu = n\pi_1 \quad \text{(Equation 9.1)}$$

$$\sigma = \sqrt{n\pi_1\pi_2} \quad \text{(Equation 9.2)}$$

When $\pi_1 = \pi_2 = .5$, the binomial distribution is symmetrical. When $\pi_1 < .5$, the distribution is positively skewed, with the degree of positive skew increasing as the value of π_1 approaches zero. When $\pi_1 > .5$, the distribution is negatively skewed, with the degree of negative skew increasing as the value of π_1 approaches one. The sampling distribution of a binomially distributed variable can be approximated by the normal distribution. The closer the value of π_1 is to .5 and the larger the value of n , the better the normal approximation. Because of the **central limit theorem** (which is discussed in Section VII of the **single-sample z test (Test 1)**), even if the value of n is small and/or the value of π_1 is close to either 0 or 1, the normal distribution still provides a reasonably good approximation of the sampling distribution for a binomially distributed variable.

The **binomial sign test for a single sample** employs the binomial distribution to determine the likelihood that x or more (or x or less) of n observations that comprise a sample will fall in one of two categories (to be designated as Category 1), if, in the underlying population, the true proportion of observations in Category 1 equals π_1 . When there are $k = 2$ categories, the hypothesis evaluated with the **binomial sign test for a single sample** is identical to that evaluated

with the **chi-square goodness-of-fit test (Test 8)**. Since the two tests evaluate the same hypothesis, the hypothesis for the **binomial sign test for a single sample** can also be stated as follows: In the underlying population represented by a sample, are the observed frequencies for the two categories different from their expected frequencies? As noted in Section I of the **chi-square goodness-of-fit test**, the **binomial sign test for a single sample** is generally employed for small sample sizes since, when the value of n is large, the computation of exact binomial probabilities becomes prohibitive without access to specialized tables or the appropriate computer software.

II. Examples

Two examples will be employed to illustrate the use of the **binomial sign test for a single sample**. Since both examples employ identical data, they will result in the same conclusions with respect to the null hypothesis.

Example 9.1 *An experiment is conducted to determine whether a coin is biased. The coin is flipped ten times resulting in eight heads and two tails. Do the results indicate that the coin is biased?*

Example 9.2 *Ten women are asked to judge which of two brands of perfume has a more fragrant odor. Eight of the women select Perfume A and two of the women select Perfume B. Is there a significant difference with respect to preference for the perfumes?*

III. Null versus Alternative Hypotheses

Null hypothesis $H_0: \pi_1 = .5$

(In the underlying population the sample represents, the true proportion of observations in Category 1 equals .5.)

Alternative hypothesis $H_1: \pi_1 \neq .5$

(In the underlying population the sample represents, the true proportion of observations in Category 1 is not equal to .5. This is a **nondirectional alternative hypothesis**, and it is evaluated with a **two-tailed test**. In order to be supported, the observed proportion of observations in Category 1 in the sample data (which will be represented with the notation p_1) can be either significantly larger than the hypothesized population proportion $\pi_1 = .5$ or significantly smaller than $\pi_1 = .5$.)³

or

$H_1: \pi_1 > .5$

(In the underlying population the sample represents, the true proportion of observations in Category 1 is greater than .5. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. In order to be supported, the observed proportion of observations in Category 1 in the sample data must be significantly larger than the hypothesized population proportion $\pi_1 = .5$.)

or

$H_1: \pi_1 < .5$

(In the underlying population the sample represents, the true proportion of observations in Category 1 is less than .5. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. In order to be supported, the observed proportion of observations in Category 1 in the sample data must be significantly smaller than the hypothesized population proportion $\pi_1 = .5$.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis is rejected.

IV. Test Computations

In Example 9.1 the null and alternative hypotheses reflect the fact that it is assumed that if one is employing a fair coin, the probability of obtaining **Heads** in any trial will equal .5 (which is equivalent to 1/2). Thus, the expected/theoretical probability for **Heads** is represented by $\pi_1 = .5$. If the coin is fair, the probability of obtaining **Tails** in any trial will also equal .5, and thus the expected/theoretical probability for **Tails** is represented by $\pi_2 = .5$. Note that $\pi_1 + \pi_2 = 1$. In Example 9.2, it is assumed that if there is no difference with regard to preference for the two brands of perfume, the likelihood of a woman selecting **Perfume A** will equal $\pi_1 = .5$ and the likelihood of selecting **Perfume B** will equal $\pi_2 = .5$. In both Examples 9.1 and 9.2 the question that is being asked is as follows: If $n = 10$ and $\pi_1 = \pi_2 = .5$, what is the probability of 8 or more observations in one of the two categories?⁴ Table 9.1 summarizes the outcome of Examples 9.1 and 9.2. The notation x is employed to represent the number of observations in Category 1 and the notation $(n - x)$ is employed to represent the number of observations in Category 2.

Table 9.1 Model for Binomial Sign Test for a Single Sample for Examples 9.1 and 9.2

Category		
1 (Heads/Perfume A)	2 (Tails/Perfume B)	Total
$x = 8$	$n - x = 10 - 8 = 2$	$n = 10$

In Examples 9.1 and 9.2, the proportion of observations in **Category/Cell 1** is $p_1 = 8/10 = .8$ (i.e., $p_1 = n_1/n$, where n_1 is the number of observations in **Category 1**), and the proportion of observations in **Category/Cell 2** is $p_2 = 2/10 = .2$ (i.e., $p_2 = n_2/n$, where n_2 is the number of observations in **Category 2**). Equation 9.3 can be employed to compute the probability that exactly x out of a total of n observations will fall in one of the two categories.

$$P(x) = \binom{n}{x} (\pi_1)^x (\pi_2)^{(n - x)} \tag{Equation 9.3}$$

The term $\binom{n}{x}$ in Equation 9.3 is referred to as the **binomial coefficient** and is computed with Equation 9.4. $\binom{n}{x}$ is more generally referred to as the **number of combinations of n things taken x at a time**.⁵

$$\binom{n}{x} = \frac{n!}{x! (n - x)!} \tag{Equation 9.4}$$

In the case of Examples 9.1 and 9.2, the binomial coefficient will be $\binom{10}{8}$, which is the combination of 10 things taken 8 at a time. In the combination expression, $n = 10$ represents the total number of coin tosses/women and $x = 8$ represents the observed frequency for Category 1 (**Heads/Perfume A**). When the latter value (which equals $\binom{10}{8} = \frac{10!}{8! 2!} = 45$) is multiplied by $(.5)^8 (.5)^2$, it yields the probability of obtaining exactly 8 **Heads/Perfume A** if there are 10 observations. The probability of 8 observations in 10 trials will be represented by the notation $P(8/10)$. The value $P(8/10) = .0439$ is computed below.

$$P(8/10) = \binom{10}{8} (.5)^8 (.5)^2 = (45)(.5)^8 (.5)^2 = .0439$$

Since the computation of binomial probabilities can be quite tedious, such probabilities are more commonly derived through the use of tables. By employing **Table A6 (Table of the Binomial Distribution, Individual Probabilities)** in the **Appendix**, the value .0439 can be obtained without any computations. The probability value .0439 is identified by employing the section of the **Table A6** for $n = 10$. Within this section, the value .0439 is the entry in the cell that is the intersection of the row $x = 8$ and the column $\pi = .5$ (where $\pi_1 = .5$ is employed to represent the value of π).

The probability .0439, however, does not provide enough information to allow one to evaluate the null hypothesis. The actual probability that is required is the likelihood of obtaining a value that is equal to or more extreme than the number of observations in Category 1. Thus, in the case of Examples 9.1 and 9.2, one must determine the probability of obtaining a frequency of 8 or greater for Category 1. In other words, we want to determine the likelihood of obtaining 8, 9, or 10 **Heads/Perfume A** if the total number of observations is $n = 10$. Since we have already determined that the probability of obtaining 8 **Heads/Perfume A** is .0439, we must now determine the probability associated with the values 9 and 10. Although each of these probabilities can be computed with Equation 9.3, it is quicker to use **Table A6**. Employing the table, we determine that for $\pi = .5$ and $n = 10$, the probability of obtaining exactly $x = 9$ observations in Category 1 is $P(9/10) = .0098$, and the probability of obtaining exactly $x = 10$ observations is $P(10/10) = .0010$. The sum of the three probabilities $P(8/10)$, $P(9/10)$, and $P(10/10)$ represents the likelihood of obtaining 8 or more **Heads/Perfume A** in 10 observations. Thus: $P(8, 9, \text{ or } 10/10) = .0439 + .0098 + .0010 = .0547$. Equation 9.5 summarizes the computation of a cumulative probability such as that represented by $P(8, 9, \text{ or } 10/10) = .0547$.⁶

$$P(\geq x) = \sum_{r=x}^n \binom{n}{r} (\pi_1)^x (\pi_2)^{(n-x)} \quad \text{(Equation 9.5)}$$

Where: $\sum_{r=x}^n$ indicates that probability values should be summed beginning with the designated value of x up through the value n

An even more efficient way of obtaining the probability $P(8, 9, \text{ or } 10/10) = .0547$ is to employ **Table A7 (Table of the Binomial Distribution, Cumulative Probabilities)** in the **Appendix**. When employing **Table A7** we again find the section for $n = 10$, and locate the cell that is the intersection of the row $x = 8$ and the column $\pi = .5$. The entry .0547 in that cell represents the probability of 8 or more (i.e., 8, 9, or 10) **Heads/Perfume A**, if there is a total of $n = 10$ observations. Thus, the entry in any cell of **Table A7** represents (for the appropriate value of π_1) the probability of obtaining a number of observations that is equal to or greater than the value of x in the left margin of the row in which the cell is located.

Table A7 can be used to determine the likelihood of x being equal to or less than a specific value. In such a case, the cumulative probability associated with the value of $(x + 1)$ is subtracted from 1. To illustrate this, let us assume that in Examples 9.1 and 9.2 we want to determine the probability of obtaining 2 or less observations in one of the two categories (which applies to Category 2). In such an instance the value $x = 2$ is employed, and thus, $x + 1 = 3$. The cumulative probability associated with $x = 3$ (for $\pi = \pi_1 = .5$) is .9453. If the latter value is subtracted from 1 it yields $1 - .9453 = .0547$, which represents the likelihood of obtaining 2 or less observations in a cell when $n = 10$.⁷ The value .0547 can also be obtained from **Table A6** by adding up the probabilities for the values $x = 2$ (.0439), $x = 1$ (.0098), and $x = 0$ (.0010).

It should be noted that none of the values listed for π in **Tables A6** and **A7** exceeds .5. To employ the tables when the value for π_1 stated in the null hypothesis is greater than .5, the following protocol is employed: a) Use the value of π_2 (i.e., $\pi_2 = 1 - \pi_1$) to represent the value of π ; and b) Each of the values of x is subtracted from the value of n , and the resulting values are employed to represent x in using the table for the analysis. To illustrate, let us assume that $n = 10$, $\pi_1 = .7$, and $x = 9$, and that we wish to determine the probability that there are 9 or more observations in one of the categories. Employing the above guidelines, the tabled value to use for π is $\pi_2 = .3$ (since $1 - .7 = .3$). Since each value of x is subtracted from n , the values $x = 9$ and $x = 10$ are respectively converted into $x = 1$ and $x = 0$. In **Table A6** (for $\pi = .3$) the probabilities associated with $x = 1$ and $x = 0$ will respectively represent those probabilities associated with $x = 9$ and $x = 10$. The sum of the tabled probabilities for $x = 1$ and $x = 0$ represents the likelihood that there will be 9 or more observations in one of the categories. From **Table A6** we determine that for $\pi = .3$, $P(1/10) = .1211$ and $P(0/10) = .0282$. Thus, $P(0 \text{ or } 1/10) = .1211 + .0282 = .1493$ (which also represents $P(9 \text{ or } 10/10)$ when $\pi_1 = .7$). The value .1493 can also be obtained from **Table A7** by subtracting the tabled probability value for $(x + 1)$ from 1 (make sure that in computing $(x + 1)$, the value of x that results from subtracting the original value of x from n is employed). Thus, if the converted value of $x = 1$, then $x + 1 = 2$. The tabled value in **Table A7** for $x = 2$ and $\pi = .3$ is .8507. When the latter value is subtracted from 1, it yields .1493.⁸

V. Interpretation of the Test Results

When the **binomial sign test for a single sample** is applied to Examples 9.1 and 9.2, it provides a probabilistic answer to the question of whether or not $p_1 = 8/10 = .8$ (i.e., the observed proportion of cases for Category 1) deviates significantly from the value $\pi_1 = .5$ stated in the null hypothesis.⁹ The following guidelines are employed in evaluating the null hypothesis.¹⁰

a) If a nondirectional alternative hypothesis is employed, the null hypothesis can be rejected if the probability of obtaining a value equal to or more extreme than x is equal to or less than $\alpha/2$ (where α represents the prespecified value of α). If the proportion $p_1 = x/n$ is greater than π_1 , a value that is more extreme than x will be any value that is greater than the observed value of x , whereas if the proportion $p_1 = x/n$ is less than π_1 , a value that is more extreme than x will be any value that is less than the observed value of x .

b) If a directional alternative hypothesis is employed that predicts the underlying population proportion is above a specified value, to reject the null hypothesis both of the following conditions must be met: 1) The proportion of cases observed in Category 1 (p_1) must be greater than the value of π_1 stipulated in the null hypothesis; and 2) The probability of obtaining a value equal to or greater than x is equal to or less than the prespecified value of α .

c) If a directional alternative hypothesis is employed that predicts the underlying population proportion is below a specified value, to reject the null hypothesis both of the following conditions must be met: 1) The proportion of cases observed in Category 1 (p_1) must be less than

the value of π_1 stipulated in the null hypothesis; and 2) The probability of obtaining a value equal to or less than x is equal to or less than the prespecified value of α .

Applying the above guidelines to the results of the analysis of Examples 9.1 and 9.2, we can conclude the following.

If $\alpha = .05$, the nondirectional alternative hypothesis $H_1: \pi_1 \neq .5$ is not supported, since the obtained probability .0547 is greater than $\alpha/2 = .05/2 = .025$. In the same respect, if $\alpha = .01$, the nondirectional alternative hypothesis $H_1: \pi_1 \neq .5$ is not supported, since the obtained probability .0547 is greater than $\alpha/2 = .01/2 = .005$.

If $\alpha = .05$, the directional alternative hypothesis $H_1: \pi_1 > .5$ is not supported, since the obtained probability .0547 is greater than $\alpha = .05$. In the same respect, if $\alpha = .01$, the directional alternative hypothesis $H_1: \pi_1 > .5$ is not supported, since the obtained probability .0547 is greater than $\alpha = .01$.

The directional alternative hypothesis $H_1: \pi_1 < .5$ is not supported, since $p_1 = .8$ is larger than the value $\pi_1 = .5$ predicted in the null hypothesis. If the alternative hypothesis $H_1: \pi_1 < .5$ is employed and the sample data are consistent with it, in order to be supported the obtained probability must be equal to or less than the prespecified value of alpha.

To summarize, the results of the analysis of Examples 9.1 and 9.2 do not allow a researcher to conclude that the true population proportion is some value other than .5. In view of this, in Example 9.1 the data do not allow one to conclude that the coin is biased. In Example 9.2, the data do not allow one to conclude that women exhibit a preference for one of the two brands of perfume.

It should be noted that if the obtained proportion $p_1 = .8$ had been obtained with a larger sample size, the null hypothesis could be rejected. To illustrate, if for $\pi_1 = .5$, $n = 15$, $x = 12$ and thus $p_1 = .8$, the likelihood of obtaining 12 or more observations in one of the two categories is .0176. The latter value is significant at the .05 level if the directional alternative hypothesis $H_1: \pi_1 > .5$ is employed, since it is less than the value $\alpha = .05$. It is also significant at the .05 level if the nondirectional alternative hypothesis $H_1: \pi_1 \neq .5$ is employed, since .0176 is less than $\alpha/2 = .05/2 = .025$.

VI. Additional Analytical Procedures for the Binomial Sign Test for a Single Sample and/or Related Tests

1. Test 9a: The z test for a population proportion When the size of the sample is large the test statistic for the **binomial sign test for a single sample** can be approximated with the chi-square distribution — specifically, through use of the **chi-square goodness-of-fit test**. An alternative and equivalent approximation can be obtained by using the normal distribution. When the latter distribution is employed to approximate the test statistic for the **binomial sign test for a single sample**, the test is referred to as the **z test for a population proportion**. The null and alternative hypotheses employed for the **z test for a population proportion** are identical to those employed for the **binomial sign test for a single sample**.

Although sources are not in agreement with respect to the minimum acceptable sample size for use with the **z test for a population proportion**, there is general agreement that the closer the value π_1 (or π_2) is to either 0 or 1 (i.e., the further removed it is from .5), the larger the sample size required for an accurate normal approximation. Among those sources that make recommendations with respect to the minimum acceptable sample size (regardless of the value of π_1) are Freund (1984) and Marascuilo and McSweeney (1977) who state that the values of both $n\pi_1$ and $n\pi_2$ should be greater than 5. Daniel (1990) states that n should be at least equal to 12. Siegel and Castellan (1988), on the other hand, note that when π_1 is close to .5, the test can be employed when $n > 25$, but when π_1 is close to 1 or 0, the value $n\pi_1\pi_2$ should be greater than

9. In view of the different criteria stipulated in various sources, one should employ common sense in interpreting results for the normal approximation based on small samples sizes, especially when the values of π_1 or π_2 are close to 0 or 1. Since, when the sample size is small the normal approximation tends to inflate the Type I error rate, the error rate can be adjusted by conducting a more conservative test (i.e., employ a lower alpha level). A more practical alternative, however, is to use a test statistic that is corrected for continuity. As will be demonstrated in the discussion to follow, when the correction for continuity is employed for the **z test for a population proportion**, the test statistic will generally provide an excellent approximation of the binomial distribution even when the size of the sample is small and/or the values of π_1 and π_2 are far removed from .5.

Examples 9.3–9.5 will be employed to illustrate the use of the **z test for a population proportion**. Since the three examples use identical data they will result in the same conclusions with respect to the null hypothesis. It will also be demonstrated that when the **chi-square goodness-of-fit test** is applied to Examples 9.3–9.5 it yields equivalent results.

Example 9.3 *An experiment is conducted to determine if a coin is biased. The coin is flipped 200 times resulting in 96 heads and 104 tails. Do the results indicate that the coin is biased?*

Example 9.4 *Although a senator supports a bill which favors a woman's right to have an abortion, she realizes her vote could influence whether or not the people in her state endorse her bid for reelection. In view of this she decides that she will not vote in favor of the bill unless at least 50% of her constituents support a woman's right to have an abortion. A random survey of 200 voters in her district reveals that 96 people are in favor of abortion. Will the senator support the bill?*

Example 9.5 *In order to determine whether or not a subject exhibits extrasensory ability, a researcher employs a list of 200 binary digits (specifically, the values 0 and 1) which have been randomly generated by a computer. The researcher conducts an experiment in which one of his assistants concentrates on each of the digits in the order it appears on the list. While the assistant does this, the subject, who is in another room, attempts to guess the value of the number for each of the 200 trials. The subject correctly guesses 96 of the 200 digits. Does the subject exhibit evidence of extrasensory ability?*

As is the case for Examples 9.1 and 9.2, Examples 9.3–9.5 are evaluating the hypothesis of whether or not the true population proportion is .5. Thus, the null hypothesis and the non-directional alternative hypothesis are: $H_0: \pi_1 = .5$ versus $H_1: \pi_1 \neq .5$.¹¹

The test statistic for the **z test for a population proportion** is computed with Equation 9.6.

$$z = \frac{p_1 - \pi_1}{\sqrt{\frac{\pi_1 \pi_2}{n}}} \quad \text{(Equation 9.6)}$$

The denominator of Equation 9.6 ($\sqrt{\pi_1 \pi_2 / n}$), which is the standard deviation of the sampling distribution of a proportion, is commonly referred to as the **standard error of the proportion**.

For Examples 9.3–9.5, based on the null hypothesis we know that: $\pi_1 = .5$ and $\pi_2 = 1 - \pi_1 = .5$. From the information that has been provided, we can compute the following values: $p_1 = 96/200 = .48$; $p_2 = (200 - 96)/200 = 104/200 = .52$. When the relevant

values are substituted in Equation 9.6, the value $z = -.57$ is computed.

$$z = \frac{.48 - .50}{\sqrt{\frac{(.5)(.5)}{200}}} = -.57$$

Equation 9.7 is an alternative form of Equation 9.6 that will yield the identical z value.

$$z = \frac{x - n\pi_1}{\sqrt{n\pi_1\pi_2}} \quad \text{(Equation 9.7)}$$

In Section I it is noted that the mean and standard deviation of a binomially distributed variable are respectively $\mu = n\pi_1$ and $\sigma = \sqrt{n\pi_1\pi_2}$. These values represent the mean and standard deviation of the underlying sampling distribution. In the numerator of Equation 9.7, the value $\mu = n\pi_1$ represents the expected number of observations in Category 1 if, in fact, the population proportion is equal to $\pi_1 = .5$ (i.e., the value stipulated in the null hypothesis). Thus, for the examples under discussion, $\mu = (200)(.5) = 100$. Note that the latter expected value is subtracted from the number of observations in Category 1. The denominator of Equation 9.7 is the standard deviation of a binomially distributed variable. Thus, in the case of Examples 9.3–9.5, $\sigma = \sqrt{(100)(.5)(.5)} = 7.07$. Employing Equation 9.7, the value $z = -.57$ (which is identical to the value computed with Equation 9.6) is obtained.

$$z = \frac{96 - (200)(.5)}{\sqrt{(200)(.5)(.5)}} = -.57$$

The obtained value $z = -.57$ is evaluated with **Table A1 (Table of the Normal Distribution)** in the **Appendix**. In **Table A1** the tabled critical two-tailed .05 and .01 values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed .05 and .01 values are $z_{.05} = 1.65$ and $z_{.01} = 2.33$.

The following guidelines are employed in evaluating the null hypothesis.

a) If the alternative hypothesis employed is nondirectional, the null hypothesis can be rejected if the obtained absolute value of z is equal to or greater than the tabled critical two-tailed value at the prespecified level of significance.

b) If the alternative hypothesis employed is directional and predicts a population proportion larger than the value stated in the null hypothesis, the null hypothesis can be rejected if the sign of z is positive and the value of z is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

c) If the alternative hypothesis employed is directional and predicts a population proportion smaller than the value stated in the null hypothesis, the null hypothesis can be rejected if the sign of z is negative and the absolute value of z is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

Using the above guidelines, the null hypothesis cannot be rejected regardless of which of the three possible alternative hypotheses is employed. The nondirectional alternative hypothesis $H_1: \pi_1 \neq .5$ is not supported, since the absolute value $z = .57$ is less than the tabled critical two-tailed value $z_{.05} = 1.96$. The directional alternative hypothesis $H_1: \pi_1 > .5$ is not supported, since to be supported, the sign of z must be positive. The directional alternative hypothesis $H_1: \pi_1 < .5$ is not supported, since although the sign of z is negative as predicted, the absolute value $z = .57$ is less than the tabled critical one-tailed value $z_{.05} = 1.65$.

It was noted previously that when there are $k = 2$ categories, the **chi-square goodness-of-fit**

test also provides a large sample approximation of the test statistic for the **binomial sign test for a single sample**. In point of fact, the large sample approximation based on the **chi-square goodness-of-fit test** will yield results that are equivalent to those obtained with the **z test for a population proportion**, and the relationship between the computed chi-square value and the obtained z value for the same set of data will always be $\chi^2 = z^2$. **Table 9.2** summarizes the results of the analysis of Examples 9.3–9.5 with the **chi-square goodness-of-fit test**, which, as noted earlier, evaluates the same hypothesis as the **binomial sign test for a single sample**. The null hypothesis and nondirectional alternative hypothesis when used in reference to the **chi-square goodness-fit-test** can also be stated employing the following format: $H_0: o_i = \epsilon_i$ for both cells versus $H_1: o_i \neq \epsilon_i$ for both cells.

Table 9.2 Chi-Square Summary Table for Examples 9.3–9.5

Cell	O_i	E_i	$(O_i - E_i)$	$(O_i - E_i)^2$	$\frac{(O_i - E_i)^2}{E_i}$
Heads/Pro-Abortion/ Correct Guesses	96	100	-4	16	.16
Tails/Anti-Abortion/ Incorrect Guesses	104	100	4	16	.16
	$\Sigma O_i = 200$	$\Sigma E_i = 200$	$\Sigma(O_i - E_i) = 0$		$\chi^2 = .32$

In **Table 9.2**, the expected frequency of each cell is computed by multiplying the hypothesized population proportion for the cell by $n = 200$ (i.e., employing Equation 8.1, $E_i = (n)(\pi_i) = (200)(.5) = 100$). Since $k = 2$, the degrees of freedom employed for the chi-square analysis are $df = k - 1 = 2$. The value $\chi^2 = .32$ (which is obtained with Equation 5.2) is evaluated with **Table A4 (Table of the Chi-Square distribution)** in the **Appendix**. For $df = 1$, the tabled critical .05 and .01 chi-square values are $\chi_{.05}^2 = 3.84$ and $\chi_{.01}^2 = 6.63$. Since the obtained value $\chi^2 = .32$ is less than $\chi_{.05}^2 = 3.84$, the null hypothesis cannot be rejected if the nondirectional alternative hypothesis $H_1: \pi_1 \neq .5$ is employed. If the directional alternative hypothesis $H_1: \pi_1 < .5$ is employed it is not supported, since $\chi^2 = .32$ is less than the tabled critical one-tailed .05 value $\chi_{.05}^2 = 2.71$ (which corresponds to the chi-square value at the 90th percentile).

As noted previously, if the z value obtained with Equations 9.6 and 9.7 is squared, it will always equal the chi-square value computed for the same data. Thus, in the current example where $z = -.57$ and $\chi^2 = .32$: $(-.57)^2 = .32$. (The minimal discrepancy is the result of rounding off error.) It is also the case that the square of a tabled critical z value at a given level of significance will equal the tabled critical chi-square value at the corresponding level of significance. This is confirmed for the tabled critical two-tailed z and χ^2 values at the .05 and .01 levels of significance: $(z_{.05} = 1.96)^2 = (\chi_{.05}^2 = 3.84)$ and $(z_{.01} = 2.58)^2 = (\chi_{.01}^2 = 6.63)$.

To summarize, the results of the analysis for Examples 9.3–9.5 do not allow one to conclude that the true population proportion is some value other than .5. In view of this, in Example 9.3 the data do not allow one to conclude that the coin is biased. In Example 9.4 the data do not allow the senator to conclude that the true proportion of the population that favors abortion is some value other than .5. In Example 9.5 the data do not allow one to conclude that the subject exhibited extrasensory abilities.

It was noted previously that when the **z test for a population proportion** is employed with small sample sizes, it tends to inflate the likelihood of committing a Type I error. This is illustrated below with the data for Examples 9.1 and 9.2 which are evaluated with Equation 9.6.

$$z = \frac{.8 - .5}{\sqrt{\frac{(.5)(.5)}{10}}} = 1.90$$

Since the obtained value $z = 1.90$ is greater than the tabled critical one-tailed value $z_{.05} = 1.65$, the directional alternative hypothesis $H_1: \pi_1 > .5$ is supported at the .05 level. When the **binomial sign test for a single sample** is employed to evaluate the latter alternative hypothesis for the same data, the result falls just short of being significant at the .05 level. The nondirectional alternative hypothesis $H_1: \pi_1 \neq .5$, which is not even close to being supported with the **binomial sign test for a single sample**, falls just short of being supported at the .05 level when the **z test for a population proportion** is employed (since the tabled critical two-tailed .05 values is $z_{.05} = 1.96$). When the conclusions reached with respect to Example 9.1 and 9.2 employing the **binomial sign test for a single sample** and the **z test for a population proportion** are compared with one another, it can be seen that the **z test for a population proportion** is the less conservative of the two tests (i.e., it is more likely to reject the null hypothesis).

The correction for continuity for z test for a population proportion It is noted in the discussions of the **Wilcoxon signed-ranks test (Test 6)** and the **chi-square goodness-of-fit test** that many sources recommend that a **correction for continuity** be employed when a continuous distribution is employed to estimate a discrete probability distribution. Most sources recommend the latter correction when the normal distribution is used to approximate the binomial distribution, since the correction will adjust the Type I error rate (which will generally be inflated when the normal approximation is employed with small sample sizes). Equations 9.8 and 9.9 are, respectively, the continuity-corrected versions of Equations 9.6 and 9.7. Each of the continuity-corrected equations is applied to the data for Examples 9.3–9.5.

$$z = \frac{|p_1 - \pi_1| - \frac{1}{2n}}{\sqrt{\frac{\pi_1\pi_2}{n}}} = \frac{|.48 - .5| - \frac{1}{(2)(200)}}{\sqrt{\frac{(.5)(.5)}{200}}} = -.49 \quad (\text{Equation 9.8})$$

$$z = \frac{|x - n\pi_1| - .5}{\sqrt{n\pi_1\pi_2}} = \frac{|96 - 100| - .5}{\sqrt{(200)(.5)(.5)}} = -.49 \quad (\text{Equation 9.9})$$

As is the case when Equations 9.6 and 9.7 are employed to compute the absolute value $z = .57$, the absolute value $z = .49$ computed with Equations 9.8 and 9.9 is less than the tabled critical two-tailed .05 value $z_{.05} = 1.96$ and the tabled critical one-tailed .05 value $z_{.05} = 1.65$. Thus, regardless of which of the possible alternative hypotheses one employs, the null hypothesis cannot be rejected. Note that the continuity-corrected absolute value $z = .49$ is less than the absolute value $z = .57$ obtained with Equations 9.6 and 9.7. Since a continuity-corrected equation will always result in a lower absolute value for z , it will provide a more conservative test of the null hypothesis. The smaller the sample size, the greater the difference between the values computed with the continuity-corrected and uncorrected equations.

Equation 8.6, which as noted previously is the continuity-corrected equation for the **chi-square goodness-of-fit test**, can also be employed with the same data and will yield an equivalent result to that obtained with Equations 9.8 and 9.9. When employing Equation 8.6 there are two cells and each cell has an expected frequency of 100. The observed frequencies of the

two cells are 96 and 104. Thus for each cell, $(|O_i - E_i| - .5) = 3.5$. Thus:

$$\chi^2 = \sum_{i=1}^k \left[\frac{(|O_i - E_i| - .5)^2}{E_i} \right] = \frac{(3.5)^2}{100} + \frac{(3.5)^2}{100} = .245$$

Note that $(.49)^2 = .245$ (once again the slight discrepancy is due to rounding off error). As is the case with $\chi^2 = .32$ (the uncorrected chi-square value computed in [Table 9.2](#)), the continuity-corrected value $\chi^2 = .245$ is not significant, since it is less than the tabled critical .05 value $\chi^2_{.05} = 3.84$ (in reference to the nondirectional alternative hypothesis).

Although in the case of Examples 9.3–9.5 the use of the correction for continuity does not alter the decision one can make with respect to the null hypothesis, this will not always be the case. To illustrate this, Equation 9.8 is employed below to compute the continuity-corrected value of z for Examples 9.1 and 9.2.

$$z = \frac{|.8 - .5| - \frac{1}{(2)(10)}}{\sqrt{\frac{(.5)(.5)}{10}}} = 1.58$$

Since the continuity-corrected value $z = 1.58$ is less than the tabled critical one-tailed value $z_{.05} = 1.65$, the directional alternative hypothesis $H_1: \pi_1 > .5$ is not supported. This is consistent with the result that is obtained when the **binomial sign test for a single sample** is employed. Recollect that when the data are evaluated with Equation 9.6 (i.e., without the continuity correction) the directional alternative hypothesis $H_1: \pi_1 > .5$ is supported. Thus, it appears that in this instance the continuity correction yields a result that is more consistent with the result based on the exact binomial probability.

Sources are not in agreement with respect to whether or not a correction for continuity should be employed. Zar (1999) cites a study by Ramsey and Ramsey (1988) which found that the results with the correction for continuity are overly conservative (i.e., more likely to retain the null hypothesis when it should be rejected).

Computation of a confidence interval for the z test for a population proportion Equation 8.5, which is described in the discussion of the **chi-square goodness-of-fit test**, can also be employed for computing a confidence interval for the **z test for a population proportion**. Equation 8.5 is employed below to compute the 95% confidence interval for Examples 9.3–9.5 for Category 1.

$$\begin{aligned} p_1 - z_{(\alpha/2)} \sqrt{\frac{p_1 p_2}{n}} &\leq \pi_1 \leq p_1 + z_{(\alpha/2)} \sqrt{\frac{p_1 p_2}{n}} \\ .48 - (1.96) \sqrt{\frac{(.48)(.52)}{200}} &\leq \pi_1 \leq .48 + (1.96) \sqrt{\frac{(.48)(.52)}{200}} \\ \pi_1 &= .48 \pm .069 \\ .411 &\leq \pi_1 \leq .549 \end{aligned}$$

Thus, the researcher can be 95% confident (or the probability is .95) that the true proportion of cases in the underlying population in Category 1 is a value between .411 and .549. The

confidence interval for the population proportion for Category 2 (i.e., π_2) can be obtained by adding and subtracting the value .069 to and from the value $p_2 = .52$. Thus, $.451 \leq \pi_2 \leq .589$.

Alternative procedures for computing a confidence interval for a binomially distributed variable are described in Zar (1999, pp. 527–530).

Extension of z test for a population proportion to evaluate the performance of m subjects on n trials on a binomially distributed variable Example 9.6 illustrates a case in which each of m subjects is evaluated for a total of n trials on a binomially distributed variable. The example represents an extension of the analysis used for Example 9.5 to a design involving m subjects. The methodology employed in analyzing the data is basically an extension of the **single-sample z test** to an analysis of a population proportion that is based on a binomially distributed variable.

Example 9.6 *In order to determine whether or not a group of 10 people exhibit extrasensory ability, a researcher employs as test stimuli a list of 200 binary digits (specifically, the values 0 and 1) which have been randomly generated by a computer. The researcher conducts an experiment in which one of his assistants concentrates on each of the digits in the order it appears on the list. While the assistant does this, each of the 10 subjects, all of whom are in separate rooms, attempts to guess the value of the number for each of 200 trials. The number of correct guesses in 200 trials for each of the subjects follows: 102, 104, 100, 98, 96, 80, 110, 120, 102, 128. Does the group as a whole exhibit evidence of extrasensory abilities?*

Equation 9.10 is employed to evaluate Example 9.6.

$$z = \frac{\bar{X} - \mu}{\frac{\sigma}{\sqrt{m}}} \quad \text{(Equation 9.10)}$$

Where: m represents the number of subjects in the sample

$$\mu = n\pi_1$$

$$\sigma = \sqrt{n\pi_1\pi_2}$$

The basic structure of Equation 9.10 is the same as that of Equation 1.3 ($z = (\bar{X} - \mu)/\sigma_{\bar{X}}$), which is the equation for the **single-sample z test**. In the numerator of Equation 1.3, the hypothesized population mean is subtracted from the sample mean. Equation 9.10 employs the analogous values — employing the sample mean (\bar{X}) and $\mu = n\pi_1$ to represent the hypothesized population mean. The denominator of Equation 1.3 represents the standard deviation of a sampling distribution that is based on a sample size of n for what is assumed to be a normally distributed variable. The denominator of Equation 9.10 represents the standard deviation of a sampling distribution of a binomially distributed variable that is based on a sample size of m . In both equations the denominator can be summarized as follows: $\sigma/\sqrt{\text{number of subjects}}$. It should also be noted that when the number of subjects is $m = 1$, Equation 9.10 reduces to Equation 9.7.¹²

Note that in Example 9.6, each of the $m = 10$ subjects is tested for $n = 200$ trials. On each trial it is assumed that a subject has a likelihood of $\pi_1 = .5$ of being correct and a likelihood of $\pi_2 = .5$ of being incorrect. Since we are dealing with a binomially distributed variable, the expected number of correct responses for each subject, as well as the expected average number of correct responses for the group of $m = 10$ subjects, is $\mu = n\pi_1$. As previously noted, the standard deviation of the sampling distribution for a single subject is defined by $\sigma = \sqrt{n\pi_1\pi_2}$.

Since there are m subjects, the standard deviation of the sampling distribution for m subjects will be σ/\sqrt{m} , which is the denominator of Equation 9.10.

The null and alternative hypotheses for Example 9.6 are identical to those employed for Example 9.5. The only difference is that, whereas in Example 9.5 H_0 and H_1 are stated in reference to the population of scores for a single subject, in Example 9.6 they are stated in reference to the population of scores for a population of subjects that is represented by the m subjects in the sample. In Example 9.6, the mean number of correct guesses by the 10 subjects is computed with Equation 1.1: $\bar{X} = 1040/10 = 104$. The values $n = 200$, $\pi_1 = .5$, $\pi_2 = .5$ are identical to those employed in Example 9.5. Thus, as is the case for Example 9.5, $\mu = (200)(.5) = 100$ and $\sigma = \sqrt{(200)(.5)(.5)} = 7.07$. When the appropriate values are substituted in Equation 9.10, the value $z = 1.79$ is computed.

$$z = \frac{104 - 100}{\frac{7.07}{\sqrt{10}}} = 1.79$$

The obtained value $z = 1.79$ is evaluated with **Table A1**. The nondirectional alternative hypothesis $H_1: \pi_1 \neq .5$ is not supported, since the value $z = 1.79$ is less than the tabled critical two-tailed value $z_{.05} = 1.96$. The directional alternative hypothesis $H_1: \pi_1 > .5$ is supported at the .05 level, since the obtained value $z = 1.79$ is a positive number that is greater than the tabled critical one-tailed value $z_{.05} = 1.65$. The latter alternative hypothesis is not supported at the .01 level, since $z = 1.79$ is less than the tabled critical one-tailed value $z_{.01} = 2.33$. The directional alternative hypothesis $H_1: \pi_1 < .5$ is not supported, since to be supported, the sign of z must be negative.

The above analysis allows one to conclude that the group as a whole scores significantly above chance. The latter result can be interpreted as evidence of extrasensory perception if one is able to rule out alternative sensory and cognitive explanations of information transmission. The reader should be aware of the fact that in spite of the conclusions with regard to the group, it is entirely conceivable that the performance of one or more of the subjects in the group is not statistically significant. Inspection of the data reveals that the performance of the subject who obtains a score of 100 is at chance expectancy. Additionally, the scores of some of the other subjects (e.g., 102, 104, 96, 98) are well within chance expectancy.¹³

It is instructive to note that in the case of Example 9.6, if for some reason one is unwilling to assume that the variable under study is binomially distributed with a standard deviation of $\sigma = 7.07$, the population standard deviation must be estimated from the sample data. Under the latter conditions the **single-sample t test (Test 2)** is the appropriate test to employ, and the following null hypothesis is evaluated: $H_0: \mu = 100$. If each of the 10 scores in Example 9.6 are squared and the squared scores are summed, they yield the value $\sum X^2 = 109728$. Employing Equation 2.1, the estimated population standard deviation is computed to be $\tilde{s} = 13.2$. Substituting the latter value, along with $\bar{X} = 104$, $\mu = 100$, and $n = 10$ in Equation 2.3 yields the value $t = .96$. Since for $df = 9$, $t = .96$ falls far short of the tabled critical two-tail .05 value $t_{.05} = 2.26$ and the tabled critical one-tail .05 value $t_{.05} = 1.83$, the null hypothesis is retained. This result is the opposite of that reached when Equation 9.10 is employed with the same data. The difference between the two tests can be attributed to the fact that in the case of the **single-sample t test** the estimated population standard deviation $\tilde{s} = 13.2$ is almost twice the value of $\sigma = 7.07$ computed for a binomially distributed variable.

2. Test 9b: The single-sample test for the median There are occasions when the **binomial sign test for a single sample** is employed to evaluate a hypothesis regarding a population median.

Specifically, the test may be used to determine the likelihood of observing a specified number of scores above versus below the median of a distribution. When the **binomial sign test for a single sample** is used within this context it is often referred to as the **single-sample test for the median**.¹⁴ This application of the **binomial sign test for a single sample** will be illustrated with Example 9.7. Since Example 9.7 assumes $\pi_1 = \pi_2 = .5$ and has the same binomial coefficient obtained for Examples 9.1 and 9.2, it yields the same result as the latter examples.

Example 9.7 *Assume that the median blood cholesterol level for a healthy 30-year-old male is 200 mg/100 ml. Blood cholesterol readings are obtained for a group consisting of eleven 30-year-old men who have had a heart attack within the last month. The blood cholesterol scores of the eleven men are: 230, 167, 250, 345, 442, 190, 200, 248, 289, 262, 301. Can one conclude that the median cholesterol level of the population represented by the sample (i.e., recent male heart attack victims) is some value other than 200?*

Since the median identifies the 50th percentile of a distribution, if the population median is in fact equal to 200, one would expect one-half of the sample to have a blood cholesterol reading above 200 (i.e., $p_1 = .5$), and one-half of the sample to have a reading below 200 (i.e., $p_2 = .5$). Although the null hypothesis and the nondirectional alternative hypothesis for Example 9.7 can be stated using the format $H_0: \pi_1 = .5$ versus $H_1: \pi_1 \neq .5$, they can also be stated as follows: $H_0: \theta = 200$ versus $H_1: \theta \neq 200$. Employing the latter format, the null hypothesis states that the median of the population the sample represent equals 200, and the alternative hypothesis states that the median of the population the sample represents does not equal 200.

When the **binomial sign test for a single sample** is employed to test a hypothesis about a population median, one must determine the number of cases that fall above versus below the hypothesized population median. Any score that is equal to the median is eliminated from the data. Employing this protocol, the score of the man who has a blood cholesterol of 200 is dropped from the data, leaving 10 scores, 8 of which are above the hypothesized median value, and 2 of which are below it. Thus, as is the case in Examples 9.1 and 9.2, we want to determine the likelihood of obtaining 8 or more observations in one category (i.e., **above the median**) if there are a total of 10 observations. It was previously determined that the latter probability is equal to .0537. As noted earlier, this result does not support the nondirectional alternative hypothesis $H_1: \pi_1 \neq .5$. It just falls short of supporting the directional alternative hypothesis $H_1: \pi_1 > .5$ (which in the case of Example 9.7 can also be stated as $H_1: \theta > 200$).

The data for Example 9.6 can also be evaluated within the framework of the **single-sample test for the median**. Specifically, if we assume a binomially distributed variable for which $\pi_1 = \pi_2 = .5$ and $\mu = 100$, the population median will also equal 100. In Example 9.6, 6 out of the 10 subjects score above the hypothesized median value $\theta = 100$, 3 score below it, and one subject obtains a score of 100. After the latter score is dropped from the analysis, 9 scores remain. Thus, we want to determine the likelihood that there will be 6 or more observations in one category (i.e., **above the hypothesized median**) if there are a total of 9 observations. Using [Table A7](#), we determine that the latter probability equals .2539. Since the value .2539 is greater than the required two-tailed .05 probability $\alpha/2 = .025$, as well as the one-tailed probability $\alpha = .05$, the null hypothesis cannot be rejected regardless of which alternative hypothesis is employed. This is in stark contrast to the decision reached when the data are evaluated with Equation 9.10. Since the latter equation employs more information (i.e., the interval/ratio scores of each subject are employed to compute the sample mean), it provides a more powerful test of an alternative hypothesis than does the **single-sample test for the median** (which conceptualizes scores as categorical data).

The **Wilcoxon signed-ranks test** also provides a more powerful test of an alternative

hypothesis concerning a population median than does the **binomial sign test for a single sample/ single-sample test for the median**.¹⁵ This will be demonstrated by employing the **Wilcoxon signed-ranks test** to evaluate the null hypothesis $H_0: \theta = 200$ for Example 9.7. Table 9.3 summarizes the analysis.

Table 9.3 Data for Example 9.7

Subject	X	$D = X - \theta$	Rank of $ D $	Signed rank of $ D $
1	230	30	2	2
2	167	-33	3	-3
3	250	50	5	5
4	345	145	9	9
5	442	242	10	10
6	190	-10	1	-1
7	200	0	-	-
8	248	48	4	4
9	289	89	7	7
10	262	62	6	6
11	301	101	8	8
				$\Sigma R+ = 51$
				$\Sigma R- = 4$

The computed Wilcoxon statistic is $T = 4$, since $\Sigma R- = 4$ (the smaller of the two values $\Sigma R-$ versus $\Sigma R+$) is employed to represent the test statistic. The value $T = 4$ is evaluated with **Table A5 (Table of Critical T Values for Wilcoxon's Signed-Ranks and Matched-Pairs Signed-Ranks Test)** in the **Appendix**. Employing **Table A5**, we determine that for $n = 10$ signed ranks, the tabled critical two-tailed .05 and .01 values are $T_{.05} = 8$ and $T_{.01} = 3$, and the tabled critical one-tailed .05 and .01 values are $T_{.05} = 10$ and $T_{.01} = 5$. Since the null hypothesis can only be rejected if the computed value $T = 4$ is equal to or less than the tabled critical value at the prespecified level of significance, we can conclude the following:

The nondirectional alternative hypothesis $H_1: \theta \neq 200$ is supported at the .05 level, since $T = 4$ is less than the tabled critical two-tailed value $T_{.05} = 8$. It is not supported at the .01 level, since $T = 4$ is greater than the tabled critical two-tailed value $T_{.01} = 3$.

The directional alternative hypothesis $H_1: \theta > 200$ is supported at both the .05 and .01 levels since: a) The data are consistent with the directional alternative hypothesis $H_1: \theta > 200$. In other words, the fact that $\Sigma R+ > \Sigma R-$ is consistent with the directional alternative hypothesis $H_1: \theta > 200$; and b) The obtained value $T = 4$ is less than the tabled critical one-tailed values $T_{.05} = 10$ and $T_{.01} = 5$.

The directional alternative hypothesis $H_1: \theta < 200$ is not supported, since it is not consistent with the data. For the latter alternative hypothesis to be supported, $\Sigma R-$ must be greater than $\Sigma R+$.

Thus, if Example 9.7 is evaluated with the **Wilcoxon signed-ranks test** the nondirectional alternative hypothesis $H_1: \theta \neq 200$ is supported at the .05 level, and the directional alternative hypothesis $H_1: \theta > 200$ is supported at both the .05 and .01 levels. When the same data are evaluated with the **binomial sign test for a single sample/single-sample test for the median**, none of the alternative hypotheses are supported (although the directional alternative hypothesis $H_1: \pi_1 > .5$ falls just short of being significant at the .05 level). From the preceding it should be apparent that the **Wilcoxon signed-ranks test** (which employs a greater amount of information) provides a more powerful test of an alternative hypothesis than does the **binomial sign test for a single sample/single-sample test for the median**.

Examination of Example 6.1 (which is identical to Example 2.1) allows us to contrast the power of the **binomial sign test for a single sample/single-sample test for the median** with the power of both the **single-sample t test** and the **Wilcoxon signed-ranks test**. When the latter problem is evaluated with the **single-sample t test**, the null hypothesis $H_0: \mu = 5$ cannot be rejected if a nondirectional alternative hypothesis is employed. However, the null hypothesis can be rejected at the .05 level if the directional alternative hypothesis $H_1: \mu > 5$ is employed. With reference to the latter alternative hypothesis, the obtained t value is greater than the tabled critical $t_{.05}$ value by a comfortable margin. When Example 6.1 is evaluated with the **Wilcoxon signed-ranks test**, the null hypothesis $H_0: \theta = 5$ cannot be rejected if a nondirectional alternative hypothesis is employed. When the directional alternative hypothesis $H_1: \theta > 5$ is employed, the analysis just falls short of being significant at the .05 level. As noted in the discussion of the **Wilcoxon signed-ranks test**, the different conclusions derived from the two tests illustrate the fact that when applied to the same data, the **single-sample t test** provides a more powerful test of an alternative hypothesis than the **Wilcoxon signed-ranks test**.

If Example 6.1 is evaluated with the **binomial sign test for a single sample/single-sample test for the median**, it would be expected that it would be the least powerful of the three tests. In Example 6.1, 7 of the 10 scores fall above the hypothesized population median $\theta = 5$ and 3 scores fall below it. Thus, using the binomial distribution we want to determine the likelihood of obtaining 7 or more observations in one category (i.e., **above the median**) if there are a total of 10 observations. Employing either **Table A6** or **A7**, we can determine that for $\pi_1 = \pi_2 = .5$ and $n = 10$, the likelihood of 7 or more observations in one category is .1719. Since the latter value is well above the required two-tailed .05 value $\alpha/2 = .025$ and the required one-tailed .05 value $\alpha = .05$, the directional alternative hypothesis $H_1: \theta > 5$ is not supported. Thus, when compared with the **Wilcoxon signed-ranks test**, which falls just short of significance, the **binomial sign test for a single sample** does not even come close to being significant.

The above noted differences between the **single-sample t test**, the **Wilcoxon signed-ranks test**, and the **binomial sign test for a single sample** illustrate that when the original data are in an interval/ratio format, the most powerful test of an alternative hypothesis is provided by the **single-sample t test** and the least powerful by the **binomial sign test for a single sample**. As noted in the **Introduction** of the book, most researchers would not be inclined to employ a nonparametric test with interval/ratio data unless one had reason to believe that one or more of the assumptions of the appropriate parametric test were saliently violated. In the same respect, unless there is reason to believe that the underlying population distribution is not symmetrical, it is more logical to employ the **Wilcoxon signed-ranks test** as opposed to the **binomial sign test for a single sample** to evaluate Example 6.1.

3. Computing the power of the binomial sign test for a single sample Cohen (1977, 1988) has developed a statistic called the **g index** that can be employed to compute the power of the **binomial sign test for a single sample** when $H_0: \pi_i = .5$ is evaluated. The **g index** represents the distance in units of proportion from the value .50. The equation Cohen (1977, 1988) employs for the **g index** is $g - P = .50$, where P represents the hypothesized value of the population proportion stated in the alternative hypothesis — in this instance it is assumed that the researcher has stated a specific value in the alternative hypothesis as an alternative to the value that is stipulated in the null hypothesis.

Cohen (1977; 1988, Ch. 5) has derived tables that allow a researcher, through use of the **g index**, to determine the appropriate sample size to employ if one wants to test a hypothesis about the distance of a proportion from the value .5 at a specified level of power. Cohen (1977; 1988, pp. 147–150) has proposed the following (admittedly arbitrary) g values as criteria for identifying the magnitude of an effect size: a) A **small effect size** is one that is greater than .05

but not more than .15; b) A **medium effect size** is one that is greater than .15 but not more than .25; and c) A **large effect size** is greater than .25.

VII. Additional Discussion of the Binomial Sign Test for a Single Sample

1. Evaluating goodness-of-fit for a binomial distribution There may be occasions when a researcher wants to evaluate the hypothesis that a set of data is derived from a binomially distributed population. Example 9.8 will be employed to demonstrate how the latter hypothesis can be evaluated with the **chi-square goodness-of-fit test**.

Example 9.8 *An animal biologist states that the probability is .25 that while in captivity a female of a species of Patagonian fox will give birth to an albino pup. Records are obtained on 100 litters each comprised of six pups (which is the modal pup size for the species) from zoos throughout the world. In 14 of the litters there were 0 albino pups, in 30 litters there was 1 albino pup, in 35 litters there were 2 albino pups, in 18 litters there were 3 albino pups, in 2 litters there were 4 albino pups, in 1 litter there were 5 albino pups, and in 0 litters there were 6 albino pups. Is there a high likelihood the data represents a binomially distributed population with $\pi_1 = .25$?*

The null and alternative hypotheses that are evaluated with the **chi-square goodness-of-fit test** in reference to Example 9.8 can either be stated in the form they are presented in Section III of the latter test (i.e., $H_0: o_i = e_i$ for all cells; $H_1: o_i \neq e_i$ for at least one cell), or as follows.

Null hypothesis H_0 : The sample is derived from a binomially distributed population, with $\pi_1 = .25$.

Alternative hypothesis H_1 : The sample is not derived from a binomially distributed population, with $\pi_1 = .25$. This is a **nondirectional alternative hypothesis**.

The analysis of Example 9.8 with the **chi-square goodness-of-fit test** is summarized in Table 9.4. The latter table is comprised of $k = 7$ cells/categories, with each cell corresponding to the number of albino pups in a litter. The second column of Table 9.4 contains the observed frequencies for albino pups. The expected frequency for each cell was obtained by employing Equation 8.1. Specifically, the value 100, which represents the total number of litters/observations, is multiplied by the appropriate binomial probability in Table A6 for a given value of x when $n = 6$ (the number of pups in a litter) and $\pi_1 = .25$. The latter binomial probabilities are as follows: $x = 0$ ($p = .1780$); $x = 1$ ($p = .3560$); $x = 2$ ($p = .2966$); $x = 3$ ($p = .1318$); $x = 4$ ($p = .0330$); $x = 5$ ($p = .0044$); $x = 6$ ($p = .0002$). Thus, if the data are binomially distributed with $\pi_1 = .25$, the following probabilities are associated with the number of albino pups in a litter comprised of 6 pups: 0 albino pups: $p = .1780$; 1 albino pup: $p = .3560$; 2 albino pups: $p = .2966$; 3 albino pups: $p = .1318$; 4 albino pups: $p = .0330$; 5 albino pups: $p = .0044$; and 6 albino pups: $p = .0002$. The expected frequencies in Column 3 of Table 9.4 are the result of multiplying each of the aforementioned binomial probabilities by 100. To illustrate the computation of an expected frequency, the value 17.80 is obtained for Row 1 (0 albino pups) as follows: $E_i = (100)(.1780) = 17.80$.

Employing Equation 8.2, the value $\chi^2 = 5.65$ is computed for Example 9.8. Since there are $k = 7$ cells and $w = 0$ parameters that are estimated, employing Equation 8.7, the degrees of freedom for the analysis are $df = 7 - 1 - 0 = 6$. Employing Table A4, we determine that for

Table 9.4 Chi-Square Summary Table for Example 9.8

Cell	O_i	E_i	$(O_i - E_i)$	$(O_i - E_i)^2$	$\frac{(O_i - E_i)^2}{E_i}$
0	14	17.80	-3.80	14.44	.81
1	30	35.60	-5.60	31.36	.88
2	35	29.66	5.34	28.52	.96
3	18	13.18	4.82	23.23	1.76
4	2	3.30	-1.30	1.69	.51
5	1	.44	.56	.31	.71
6	0	.02	-.02	.0004	.02
$\Sigma O_i = 100$ $\Sigma E_i = 100$ $\Sigma(O_i - E_i) = 0$			$\chi^2 = 5.65$		

$df = 6$ the tabled critical .05 and .01 values are $\chi^2_{.05} = 12.59$ and $\chi^2_{.01} = 16.81$. Since the computed value $\chi^2 = 5.65$ is less than both of the aforementioned values, the null hypothesis cannot be rejected. Thus, the analysis does not indicate that the data deviate significantly from a binomial distribution.

It should be noted that if, instead of stipulating the value $\pi_1 = .25$, the population proportion had been estimated from the sample data, the value of df is reduced by 1 (i.e., $df = 7 - 1 - 1 = 5$). The latter is the case, since an additional degree of freedom must be subtracted for the parameter that is estimated. In Example 9.8 the proportion of albino pups is $p_1 = n_1/N = 167/600 = .278$ (where n_1 is the total number of albino pups, and N is the total number of pups in the 100 litters ($N = (6)(100) = 600$)). The value $n_1 = 167$ is computed as follows: a) In each row of Table 9.4, multiply the value for the number of albino pups in Column 1 by the observed frequency for that number of albino pups in Column 2; and b) Sum the seven products obtained in a). The latter sum will equal the total number of albino pups and, if that value is divided by the total number of pups (N), it yields the value p_1 . The latter value will represent the best estimate of the population proportion π_1 .

It is important to note that if the value .278 is employed to represent π_1 , the expected frequencies will be different from those recorded in Column 3 of Table 9.4. Since the value $\pi_1 = .278$ is not listed in Table A6, the latter table cannot be employed to determine the binomial probabilities to employ in computing the expected frequencies. Consequently we would have to employ Equation 9.3 to compute the appropriate binomial probabilities for the values of x (i.e., 0, 1, 2, 3, 4, 5, and 6) when $n = 6$, $\pi_1 = .278$ and $\pi_2 = 1 - .278 = .722$, and then use the resulting binomial probabilities to compute the expected frequencies (once again by multiplying each probability by 100).

VIII. Additional Example Illustrating the Use of the Binomial Sign Test for a Single Sample

Example 9.9 employs the **binomial sign test for a single sample** in a case where the value of π_1 stated in the null hypothesis is close to 1. It also illustrates that the continuity-corrected version of the **z test for a population proportion** can provide an excellent approximation of the binomial distribution, even if the value of π_1 is far removed from .5.

Example 9.9 *A biologist has a theory that 90% of the people who develop a rare disease are males and only 10% are females. Of 10 people he identifies who have the disease, 7 are males and 3 are females. Do the data support the biologist's theory?*

Since the information given indicates that we are dealing with a binomially distributed variable with $\pi_1 = .9$ and $\pi_2 = .1$, the data can be evaluated with the **binomial sign test for a single sample**. Based on the biologist's theory, the null hypothesis and the nondirectional alternative hypothesis are as follows: $H_0: \pi_1 = .9$ versus $H_1: \pi_1 \neq .9$. The data consist of the number of observations in the two categories **males** versus **females**. The respective proportion of observations in the two categories are: $p_1 = 7/10 = .7$ and $p_2 = 3/10 = .3$. Thus, given that $\pi_1 = .9$, we want to determine the likelihood of 7 or fewer observations in one category if there are a total of 10 observations. Note that since $p_1 = .7$ is less than $\pi_1 = .9$, a value that is more extreme than $x = 7$ will be any value that is less than 7.

Since $\pi = \pi_1 = .9$ is not listed in either **Table A6** or **A7**, we employ for π the probability value listed for π_2 , which in the case of Example 9.9 is $\pi_2 = .1$. The probability of x being equal to or less than 7 (i.e., the number of observations in Category 1) if $\pi_1 = .9$, will be equivalent to the probability of x being equal to or greater than 3 (which is the number of observations in Category 2) if $\pi_2 = .1$. From **Table A7** it can be determined that the latter probability (which is in the cell that is the intersection of the row $x = 3$ and the column $\pi = .1$) is equal to .0702. The same value can be obtained from **Table A6** by adding the probabilities for all values of x equal to or greater than 3 (for $\pi = .1$). Thus, the probability of 7 or fewer males if there is a total of 10 observations is .0702.¹⁶ Since the latter value is greater than the two-tailed .05 value $\alpha/2 = .025$ and the one-tailed .05 value $\alpha = .05$, neither the nondirectional alternative hypothesis $H_1: \pi_1 \neq .9$ nor the directional alternative hypothesis which is consistent with the data ($H_1: \pi_1 < .9$) is supported. In other words, $p_1 = .7$ (the observed proportion of males) is not significantly below the hypothesized value $\pi_1 = .9$. In the same respect $p_2 = .3$, the observed proportion of females, is not significantly above the expected value of $\pi_2 = .1$.

When the **z test for a population proportion** is employed to evaluate Example 9.9, Equation 9.6 (which does not employ the correction for continuity) yields the following result: $z = (.7 - .9)/\sqrt{[(.9)(.1)]/10} = -2.11$. Equation 9.8 (the continuity-corrected equation) has the identical denominator as Equation 9.6, but the numerator is reduced by $1/[(2)(10)] = .05$, thus yielding the value $z = -1.58$. Since the absolute value $z = 2.11$ is greater than the tabled critical two-tailed .05 value $z_{.05} = 1.96$ and the tabled critical one-tailed .05 value $z_{.05} = 1.65$, without the correction for continuity both the nondirectional alternative hypothesis $H_1: \pi_1 \neq .9$ and the directional alternative hypothesis $H_1: \pi_1 < .9$ are supported at the .05 level. When the correction for continuity is employed, the obtained absolute value $z = 1.58$ is less than both of the aforementioned tabled critical values and, because of this, regardless of which alternative hypothesis is employed, the null hypothesis cannot be rejected. The latter conclusion is consistent with the result obtained when the exact binomial probabilities are employed. Thus, even in a case where the value of π_1 is far removed from .5, the continuity-corrected equation for the **z test for a population proportion** appears to provide an excellent estimate of the exact binomial probability.

IX. Addendum

Discussion of additional discrete probability distributions In this section a number of other discrete probability distributions are described, some of which are related to the binomial distribution. The following distributions will be discussed: a) The **multinomial distribution**; b) The **negative binomial distribution**; c) The **hypergeometric distribution**; d) The **Poisson distribution**; and d) The **matching distribution**.

1. The multinomial distribution Earlier in this chapter it was noted that: a) The binomial distribution is a special case of the **multinomial distribution**; b) The **multinomial distribution** is

an extension of the binomial model to two or more categories; and c) The **multinomial distribution** is the exact probability distribution that the **chi-square goodness-of-fit test** is employed to estimate (for two or more categories).

The conditions that describe the model for the multinomial distribution are that on each of n independent trials there are k possible outcomes. The probability on any trial that an outcome will fall in the i^{th} category is π_i . Thus, the probabilities for the k categories are $\pi_1, \pi_2, \pi_3, \dots, \pi_k$. As is the case with the binomial distribution, sampling with replacement (which is defined in Endnote 1) is assumed for the multinomial distribution.

Equation 9.11 is a multinomial generalization of Equation 9.3 (the binomial equation for computing the probability for a specific value of x) that can be employed when there are two or more categories. Equation 9.11 computes the probability that in n independent trials, n_1 outcomes will fall in Category 1, n_2 outcomes will fall in Category 2, n_3 outcomes will fall in Category 3, ..., and n_k outcomes will fall in Category k . The term $n! / (n_1! n_2! n_3! \dots n_k!)$ on the right side of Equation 9.11 is referred to as the **multinomial coefficient**. The multinomial analog of the binomial expansion $(\pi_1 + \pi_2)^n$ (discussed in Endnote 6) is the multinomial expansion described by the general equation $(\pi_1 + \pi_2 + \pi_3 + \dots + \pi_k)^n$.

(Equation 9.11)

$$P(n_1, n_2, n_3, \dots, n_k) = \frac{n!}{n_1! n_2! n_3! \dots n_k!} (\pi_1^{n_1}) (\pi_2^{n_2}) (\pi_3^{n_3}) \dots (\pi_k^{n_k})$$

When $k = 2$, Equation 9.11 reduces to Equation 9.3. Thus, using Equation 9.11 we can compute the binomial probability .0439 for $x = 8$ computed for Examples 9.1/9.2 in Section IV.

$$P(n_1 = 8, n_2 = 2) = \frac{n!}{n_1! n_2!} (\pi_1)^{n_1} (\pi_2)^{n_2} = \frac{10!}{8! 2!} (.5)^8 (.5)^2 = .0439$$

Examples 9.10, 9.11, and 9.12 will be employed to illustrate the application of Equation 9.11 to compute a multinomial probability.

Example 9.10 *An automobile dealer gets a delivery of ten cars. The company that manufactures the cars only delivers cars of the following three colors: silver, red, and blue. Assume that the likelihood of a car being silver, red, or blue is as follows: Silver (.2), Red (.3), and Blue (.5). What is the probability that of the ten cars delivered, five will be silver, four will be red, and one will be blue?*

In Example 9.10 there are $n = 10$ observations/trials which correspond to the total of ten cars, and there are the following three categories: Category 1 – Silver cars; Category 2 – Red cars; Category 3 – Blue cars. Thus, $\pi_1 = .2$, $\pi_2 = .3$, and $\pi_3 = .5$. Since we are asking what the probability is that there will be five silver cars, four red cars, and one blue car, we can stipulate the values $n_1 = 5$, $n_2 = 4$, and $n_3 = 1$. Substituting the appropriate values in Equation 9.11, we determine that the probability of the delivery being comprised of five silver cars, four red cars, and one blue car is .0016.

$$P(n_1 = 5, n_2 = 4, n_3 = 1) = \frac{10!}{(5!)(4!)(1!)} (.2)^5 (.3)^4 (.5)^1 = .0016$$

Example 9.11 Assume that during an official time at bat a major league baseball player has a .65 chance of making out, a .18 chance of hitting a single, a .07 chance of hitting a double, a .01 chance of hitting a triple, and a .09 chance of hitting a home run. If, during a game, the player has six official at bats, what is the likelihood that he will make out in all six at bats?

In Example 9.11 there are $n = 6$ observations/trials which correspond to the six at bats, and there are the following five categories: Category 1 – Out; Category 2 – Single; Category 3 – Double; Category 4 – Triple; Category 5 – Home run. Thus, $\pi_1 = .65$, $\pi_2 = .18$, $\pi_3 = .07$, $\pi_4 = .01$, $\pi_5 = .09$. Since we are asking what the probability is that there will be six outs, zero singles, zero doubles, zero triples, and zero home runs, we can stipulate the values $n_1 = 6$, $n_2 = 0$, $n_3 = 0$, $n_4 = 0$, and $n_5 = 0$. Substituting the appropriate values in Equation 9.11, we determine that the probability of the player making out six times is .075.

$$P(n_1 = 6, n_2 = 0, n_3 = 0, n_4 = 0, n_5 = 0) = \frac{6!}{(6!)(0!)(0!)(0!)(0!)} (.65)^6 (.18)^0 (.07)^0 (.01)^0 (.09)^0 = .075$$

Example 9.12 A bird watcher spends the day searching for a particular species of bird whose beak can be either red or white and whose tail can be either long or short. Assume that the likelihood of a bird having a red beak and long tail is .10, the likelihood of a bird having a red beak and a short tail is .30, the likelihood of a bird having a white beak and long tail is .40, and the likelihood of a bird having a white beak and short tail is .20. If the bird watcher spots three birds of the species in question, what is the probability of observing three birds that conform to the characteristics noted in [Table 9.5](#)?

Table 9.5 Data for Example 9.12

		Tail Size	
		Long Tail	Short Tail
Beak Color	Red	0	1
	White	1	1

In Example 9.12 there are $n = 3$ observations/trials that correspond to the total of three birds, and there are the following four categories: Category 1 – Red beak/Long Tail; Category 2 – Red beak/Short tail; Category 3 – White beak/Long Tail; Category 4 – White beak/Short Tail. Thus, $\pi_1 = .1$, $\pi_2 = .3$, $\pi_3 = .4$, and $\pi_4 = .2$. Since we are asking what the probability is that there will be zero birds with a Red beak/Long tail, one bird with a Red beak/Short Tail, one bird with a White beak/Long tail, and one bird with a White beak/Short tail, we can stipulate the values $n_1 = 0$, $n_2 = 1$, $n_3 = 1$, and $n_4 = 1$. Substituting the appropriate values in Equation 9.11 we determine that the probability of the bird watcher sighting the three birds noted in [Table 9.5](#) is .144.

$$P(n_1 = 0, n_2 = 1, n_3 = 1, n_4 = 1) = \frac{3!}{(0!)(1!)(1!)(1!)} (.1)^0 (.3)^1 (.4)^1 (.2)^1 = .144$$

In point of fact, if the bird watcher spots three birds, there are 20 possible configurations of beak color and tail length (which we assume are independent of one another) for which we can compute a multinomial probability. The 20 configurations are summarized in [Table 9.6](#) along with their probabilities. Note that the probability value associated with each of the configurations

is quite low, and that the sum of the probability values for all of the configurations adds up to 1. If analogous tables were constructed for Examples 9.10 and 9.11 (in which there are, respectively, ten and six observations), the number of possible configurations would be substantially larger than the 20 configurations for Example 9.12 (which has only three observations).

The values recorded in Columns 2–5 of [Table 9.6](#) represent the number of birds who possess the beak and tail characteristic noted at the top of a column. The configuration represented in [Table 9.5](#), for which the probability .144 is computed, corresponds to **Configuration 19** in [Table 9.6](#).

Table 9.6 Color/Tail Configuration for $n = 3$ Birds

Configuration	Red Beak/ Long Tail	Red Beak/ Short Tail	White Beak/ Long Tail	White Beak/ Short Tail	Multinomial Probability
1	3	0	0	0	.001
2	0	3	0	0	.027
3	0	0	3	0	.064
4	0	0	0	3	.008
5	2	1	0	0	.009
6	0	0	2	1	.096
7	2	0	1	0	.012
8	0	2	0	1	.054
9	1	2	0	0	.027
10	0	0	1	2	.048
11	1	0	2	0	.048
12	0	1	0	2	.036
13	0	2	1	0	.108
14	2	0	0	1	.006
15	0	1	2	0	.144
16	1	0	0	2	.012
17	1	1	1	0	.072
18	1	1	0	1	.036
19	0	1	1	1	.144
20	1	0	1	1	.048
Sum = 1.000					

2. The negative binomial distribution The **negative binomial distribution** is another discrete probability distribution that can be employed within the context of evaluating certain experimental situations. As is the case with the binomial distribution, the model for the negative binomial distribution assumes the following: a) In a set of n independent trials there are only two possible outcomes; and b) Sampling with replacement. If we identify the two outcomes as Category 1 and Category 2, the negative binomial distribution allows us to determine the probability that exactly n trials will be required to obtain x observations in Category 1. If π_1 represents the likelihood that an observation will fall in Category 1, and π_2 represents the likelihood that an observation will fall in Category 2, the probability that exactly n trials will be required to obtain x observations in Category 1 is computed with Equation 9.12.

$$P(x) = \binom{n-1}{x-1} \pi_1^x \pi_2^{n-x} \quad (\text{Equation 9.12})$$

Although there are special tables prepared by Williamson and Bretherton (1963) for obtaining negative binomial probabilities, the latter values can also be determined through use of tables for the binomial distribution. Miller and Miller (1999) note that the probabilities in [Table A6](#) can

be employed to determine a negative binomial probability computed with Equation 9.12, by multiplying the individual probability associated with x in [Table A6](#) by (x/n) . Guenther (1968) notes that the negative binomial probability that n or fewer trials will be required to obtain x observations in Category 1 is equivalent to the cumulative binomial probability (in [Table A7](#)) for x or more observations in n trials. Thus, in [Table A7](#), for the appropriate value of π_1 , one would find the cumulative probability associated with x for a given value of n .

Examples 9.13 and 9.14 will be employed to illustrate the application of Equation 9.12 to compute a negative binomial probability.

Example 9.13 *The likelihood on any trial that a copy machine will print an acceptable copy is only .25. What is the probability that exactly 12 copies will have to be printed before five acceptable copies are printed by the machine? What is the probability that the fifth acceptable copy will be printed on or before the twelfth trial? What is the probability that the fifth acceptable copy will be printed after the twelfth trial?*

Based on the information that has been provided in Example 9.13, we can stipulate the following values that we will employ in Equation 9.12: $n = 12$, $x = 5$, $\pi_1 = .25$, and $\pi_2 = .75$. Substituting the appropriate values in Equation 9.12, we compute the probability $p = .04317$. The latter value can also be obtained from [Table A6](#) by doing the following: a) Go to the section for $n = 12$; b) Find the probability in the cell that is the intersection of the row $x = 5$ and the column $\pi = .25$ (i.e., obtain the probability of five observations in 12 trials) — the latter value is .1032; and c) Multiply the probability obtained in b) (i.e., .1032) by (x/n) . The resulting value will represent the likelihood of requiring exactly 12 trials to print five acceptable copies. Thus, $(.1032)(5/12) = .043$.

$$P(r) = \left(\frac{12 - 1}{5 - 1} \right) (.25)^5 (.75)^7 = \left(\frac{11}{4} \right) (.25)^5 (.75)^7 = .04317$$

Example 9.13 also asks for the probability that the fifth acceptable copy will be printed on or before the twelfth trial, and the probability that the fifth acceptable copy will be printed after the twelfth trial. As noted earlier, the probability that the x^{th} acceptable copy will be printed on or before the n^{th} trial will correspond to the cumulative binomial probability for $n = 12$, $x = 5$, and $\pi_1 = .25$ in [Table A7](#) (which contains the probabilities computed with Equation 9.5). In the latter table the appropriate cumulative probability is .1576, which, in the case of Example 9.13, represents the likelihood that the fifth acceptable copy will be printed on or before the twelfth trial. We can also compute the probability that the fifth acceptable copy will be printed on or before the twelfth trial by employing Equation 9.12 with all values of n between five (which is the fewest possible trials in which five acceptable copies can be printed) and twelve, and summing the individual probabilities. When the values five through twelve are substituted for x in Equation 9.12, the following probability values are obtained which sum to .1576 (the minimal difference between the sum of the listed values and .1576 is due to rounding off error): $x = 5$ ($p = .00098$); $x = 6$ ($p = .003675$); $x = 7$ ($p = .00827$); $x = 8$ ($p = .01447$); $x = 9$ ($p = .02171$); $x = 10$ ($p = .02930$); $x = 11$ ($p = .03663$); $x = 12$ ($p = .04317$).

The answer to the last question posed in Example 9.13 (the likelihood that the fifth acceptable copy will be printed after the twelfth trial) is obtained simply by subtracting the value .1576 from 1. Thus, $1 - .1576 = .8424$ is the likelihood the fifth acceptable copy will be printed after the twelfth trial.

Equation 9.13 can be employed to compute the expected value (μ) for a negative binomially distributed variable. μ represents the expected number of trials to obtain x outcomes in

Category 1. The standard deviation of a negative binomially distributed variable is computed with Equation 9.14. In the case of Example 9.13, the values $\mu = 20$ and $\sigma = 7.75$ are computed. Thus, if we conducted an infinite number of experiments with the copier, and in each experiment we printed copies until five were acceptable, the average value for n (i.e., the average number of trials required to obtain five acceptable copies) will be 20, and the standard deviation of the sampling distribution will equal 7.75.

$$\mu = \frac{x}{\pi_1} = \frac{5}{.25} = 20 \quad (\text{Equation 9.13})$$

$$\sigma = \frac{\sqrt{x\pi_2}}{\pi_1} = \frac{\sqrt{(5)(.75)}}{(.25)} = 7.75 \quad (\text{Equation 9.14})$$

Example 9.14 *The likelihood that a basketball player will put the ball in the basket each time he shoots is .25. What is the probability that the player will have to take exactly 12 shots before making five baskets? What is the probability that the fifth successful shot will be made on or before the twelfth shot? What is the probability that the fifth successful shot will be made after the twelfth shot?*

Since the data for Example 9.14 are identical to that employed for Example 9.13, it yields the same probabilities. Thus, the probability of requiring exactly 12 shots to make five baskets is .043. The probability that the fifth successful shot will occur on or before the twelfth shot is .1576. The probability that the fifth successful shot will occur after the twelfth shot is .8424.

3. The hypergeometric distribution The model for the **hypergeometric distribution** is similar to the model for the binomial distribution except for one critical difference — the latter being that in the hypergeometric model **sampling without replacement** (which is defined in Endnote 1) is assumed. In the hypergeometric model, in a set of n trials there are two possible outcomes (to be designated Category 1 versus Category 2), and because sampling without replacement is assumed, the outcome on each trial will be dependent on the outcomes of previous trials. The latter will be the case since, if there are two categories, the probability of obtaining an outcome in a given category will change from trial to trial and, on any trial, the value of the probabilities will be a function of the number of potential observations in each category that are still available to be selected.

Equation 9.15 is employed to compute a hypergeometric probability. The equation assumes there is a population comprised of N objects, each of which falls into one of two categories. In the population there are N_1 objects in Category 1, and N_2 objects in Category 2. Let us assume that we want to select a sample of n objects from the population employing sampling without replacement. We select x objects from Category 1, and $(n - x)$ objects from Category 2. Equation 9.15 allows us to compute the probability that we will select exactly x objects from Category 1 and $(n - x)$ objects from Category 2.

$$P(x) = \frac{\binom{N_1}{x} \binom{N_2}{n-x}}{\binom{N}{n}} \quad (\text{Equation 9.15})$$

Examples 9.15 and 9.16 will be employed to illustrate the computation of a hypergeometric probability with Equation 9.15.

Example 9.15 What is the probability of selecting two boys and one girl from a class of nine students that consists of five boys and four girls?

Example 9.16 A researcher predicts that people who suffer from migraine headaches who take 500 milligrams of vitamin E daily are more likely to show a remission of symptoms than patients who don't take the vitamin. Nine patients with a history of migraines participate in a study. Five of the patients take 500 milligrams of vitamin E daily for a period of six months, while the other four patients, who comprise a control group, do not take a vitamin E supplement. At the conclusion of the study, two patients in the vitamin E group exhibit a remission of symptoms, while one person in the control group exhibits a remission of symptoms. What is the probability of this outcome?

In both of the above examples we are dealing with a population that is comprised of $N = 9$ students/patients. There are $N_1 = 5$ students/patients in Category 1, and $N_2 = 4$ students/patients in Category 2. We let $x = 2$ represent the two boys/patients in the vitamin E group who exhibits symptom remission. Thus, $n - x = 3 - 2 = 1$ represents the one girl/patient in the control group who exhibits symptom remission. Employing Equation 9.15, the value .4762 is computed below for the probability of selecting two boys and one girl, or two patients in the experimental group exhibiting remission and one patient in control group exhibiting remission.

$$P(x = 2) = \frac{\binom{5}{2}\binom{4}{1}}{\binom{9}{3}} = .4762$$

In the case of Example 9.16, we want to determine whether there is a significant difference between the response of the vitamin E group and the control group. The null hypothesis is that there is no difference between the two groups. In order to evaluate the null hypothesis, we must compute the chance likelihood/probability of obtaining an outcome equal to or more extreme than the outcome observed in the study. In order to determine the latter, we must compute the hypergeometric probabilities for all possible outcomes involving the value $n = 3$. Specifically, the following four outcomes can be obtained in which three out of a total of nine patients exhibit a remission of symptoms: a) All three patients who exhibit remission are in the vitamin E group; b) Two of the three patients who exhibit remission are in the vitamin E group, and the remaining patient is in the control group; c) One of the three patients who exhibit remission are in the vitamin E group, and the remaining two patients are in the control group; and d) All three patients who exhibit remission are in the control group. Note that Outcome **b** noted above corresponds to the observed outcome in Example 9.16, and that the sum of the probabilities for the four outcomes is equal to 1 (due to rounding off error, the four probabilities sum to .9999). The hypergeometric probabilities for all four possible outcomes when $n = 3$ are noted below.

$$\begin{array}{ll} \text{a) } P(x = 3) = \frac{\binom{5}{3}\binom{4}{0}}{\binom{9}{3}} = .1190 & \text{b) } P(x = 2) = \frac{\binom{5}{2}\binom{4}{1}}{\binom{9}{3}} = .4762 \\ \text{c) } P(x = 1) = \frac{\binom{5}{1}\binom{4}{2}}{\binom{9}{3}} = .3571 & \text{d) } P(x = 0) = \frac{\binom{5}{0}\binom{4}{3}}{\binom{9}{3}} = .0476 \end{array}$$

If a directional alternative hypothesis is employed (i.e., a one-tailed analysis is conducted), the null hypothesis can be rejected if the following conditions are met: a) The obtained difference is in the predicted direction; and b) The probability of obtaining a value equal to or more extreme than $x = 2$ is equal to or less than the value of α (which we will assume is .05). The data are consistent with the directional alternative hypothesis which predicts a better response by the vitamin E group. However, Outcome **a** is in the same direction and more extreme than Outcome **b**. Thus, if we add the probabilities for Outcomes **a** and **b**, we obtain $.1190 + .4762 = .5952$. Since the latter value is greater than $\alpha = .05$, the null hypothesis cannot be rejected. Thus, we cannot conclude that vitamin E had a therapeutic effect.

If a nondirectional alternative hypothesis is employed (i.e., a two-tailed analysis is conducted), the null hypothesis can be rejected if the probability of obtaining a value equal to or more extreme than $x = 2$ is equal to or less than the prespecified level of significance. In the case of a two-tailed analysis, however, we take into account more extreme outcomes in either direction. In actuality, all of the outcomes are more extreme than Outcome **b**. The latter is the case, since in Outcomes **a**, **c**, and **d**, the proportion of subjects in the group that exhibits remission for two or more subjects is higher than the proportion $2/5 = .40$ for the vitamin E group in Outcome **b**. Because all of the other outcomes are more extreme than the observed outcome, the null hypothesis cannot be rejected. Use of the hypergeometric distribution in hypothesis testing is discussed in greater detail within the framework of the **Fisher exact test (Test 16c)** (which is discussed in Section VI of the **chi-square test for $r \times c$ tables (Test 16)**).

Equation 9.16 can be employed to compute the expected value (μ) of a hypergeometrically distributed random variable (μ is generally only computed for Category 1). In the case of Examples 9.15/9.16, the latter value is computed to be $\mu = 1.67$. The value $\mu = 1.67$ represents the expected number of outcomes in Category 1, when $n = 3$. If $N_2 = 4$ is employed in Equation 9.16 in place of N_1 , the value $\mu = 1.33$ is computed, which represents the expected number of outcomes in Category 2, when $n = 3$. Note that when $\mu = 1.67$ is subtracted from 3, the resulting value is $\mu = 1.33$.

$$\mu = \frac{nN_1}{N} = \frac{(3)(5)}{9} = 1.67 \quad \text{(Equation 9.16)}$$

Equation 9.17 can be employed to compute the expected value of the standard deviation (σ) of a hypergeometrically distributed random variable (σ is generally only computed for Category 1). In the case of Examples 9.15/9.16, the latter value is computed to be $\sigma = .745$. The identical value will be obtained for σ if N_2 is employed in Equation 9.17 in place of N_1 .

(Equation 9.17)

$$\sigma = \sqrt{n \left(\frac{N_1}{N} \right) \left(1 - \frac{N_1}{N} \right) \left(\frac{N - n}{N - 1} \right)} = \sqrt{3 \left(\frac{5}{9} \right) \left(1 - \frac{5}{9} \right) \left(\frac{9 - 3}{9 - 1} \right)} = .745$$

When the value of N is very large relative to the value of n , the binomial distribution provides an excellent approximation of the hypergeometric distribution. This is the case, since, under the latter conditions, the differences between the sampling without replacement model and sampling with replacement model are minimized. To further clarify the relationship between the binomial and hypergeometric distributions, in Equation 9.16 the element N_1/N represents the proportion of cases in Category 1 in a dichotomous distribution. Thus, if we represent the element N_1/N with the notation π_1 (since it represents the same thing π_1 is employed to

represent for the binomial distribution), an alternative way of writing Equation 9.16 is $\mu = np$, which is the same as Equation 9.1, the equation for computing the expected value of a binomially distributed variable.

Now let us turn our attention to Equation 9.17. Once again we can employ π_1 to represent the element N_1/N . The element $1 - (N_1/N)$ represents the proportion of cases in Category 2, and thus we can represent it with the notation π_2 (because $\pi_2 = 1 - \pi_1$), since it represents the same thing π_2 represents for the binomial distribution. If the value of n is very small relative to the value of N , the element $(N - n)/(N - 1)$ will approach the value 1. If the latter is true, Equation 9.17 can be written as $\sigma = \sqrt{n\pi_1\pi_2}$, which is identical to Equation 9.2, the equation for computing the standard deviation of a binomially distributed variable.

Daniel and Terrell (1995) state that as a general rule, in order to get a reasonable binomial approximation for a hypergeometrically distributed variable, the value of N should be at least ten times as large as the value of n . To illustrate the binomial approximation, let us consider the following values for a hypergeometrically distributed variable: $N = 40$, $N_1 = 10$, $N_2 = 30$, $n = 3$, $x = 1$. When the hypergeometric probability for $x = 1$ is computed below, we obtain the value $p = .4403$.

$$P(x = 1) = \frac{\binom{10}{1}\binom{30}{2}}{\binom{40}{3}} = .4403$$

Employing [Table A6](#), we can determined the binomial probability for $x = 1$ when $n = 3$, $\pi_1 = .25$ (since $N_1/N = 10/40 = .25$), and $\pi_2 = .75$ (since $N_2/N = 30/40 = .75$). The latter value, which is also computed below with Equation 9.3, is .4219 (which is very close to the exact hypergeometric probability of .4403 computed above).

$$P(x = 1) = \binom{n}{x}(\pi_1)^x(\pi_2)^{(n-x)} = \binom{3}{1}(.25)(.75)^2 = .4219$$

4. The Poisson distribution With the exception of the binomial distribution, the **Poisson distribution** is probably the most commonly employed discrete probability distribution. The latter distribution is named after the French mathematician Simeon Denis Poisson, who described it in the 1830s (although Zar (1999) notes that it was described previously by another mathematician, Abraham de Moivre, in 1718). The Poisson distribution (which Pagano and Gauvreau (1993) note is sometimes referred to as the **distribution of rare events**) is most commonly employed in evaluating a distribution of random events that have a low probability of occurring. The Poisson distribution is employed most frequently in situations where there is an interest in the number of times a particular event occurs within a specified period of time or within a specific physical environment. Feller (1968) and Guenther (1968) cite the following as examples of random events whose behavior is consistent with the Poisson distribution: a) The number of automobile accidents per month in a large city; b) The number of meteorites that land in areas of fixed size in a desert; c) The number of typographical errors per page in a manuscript; d) The number of telephone calls a person receives in a 24-hour period; e) The number of defective products manufactured daily on an assembly line; f) The number of atoms per second that disintegrate from a radioactive substance; and g) The number of bombs that hit specified blocks of equal area in London during World War II.

The model for the Poisson distribution assumes that within a given time period or within a give area, the likelihood of a random event occurring (with the occurrence of events being

independent of one another) is very low. Consequently if we have an infinite number of time periods or an infinite block of areas, the likelihood of more than one event occurring within any time period or area is very small (although, theoretically, there is no limit on the number of events that can occur within a specific time period/area).

A Poisson distribution has what is referred to as a parameter (or sometimes referred to as a **rate parameter**), which is represented by the notation λ (which is the lower case Greek letter **lambda**). The parameter λ is the average number of events that occur over a given period of time or within a specified area of space. λ also happens to be the variance of a Poisson distributed variable. Thus, Equations 9.18 and 9.19 define the mean/expected value (μ) and variance of a Poisson distribution

$$\mu = \lambda \quad \text{(Equation 9.18)}$$

$$\sigma^2 = \lambda \quad \text{(Equation 9.19)}$$

It can be seen from inspection of Equations 9.18 and 9.19 that in a Poisson distribution $\mu = \sigma^2$, and because of the latter it is often assumed that any distribution where $\mu = \sigma^2$ is likely to be Poisson. Equation 9.20 is the general equation for computing a probability for the Poisson distribution. The latter equation computes the probability of x events occurring in a given period of time or within a specified area of space. Since x is a measure of a discrete random variable, any value obtained for x will have to be an integer number.

$$P(X = x) = \frac{e^{-\mu} \mu^x}{x!} \quad \text{(Equation 9.20)}$$

Example 9.17 will be employed to illustrate the computation of a Poisson probability with Equation 9.20.

Example 9.17 *The traffic bureau of a Midwestern city claims that on the average two accidents occur per day, and that the frequency distribution of accidents conforms to a Poisson distribution. If the latter is true, what are the probabilities for the following numbers of accidents occurring per day: 0, 1, 2, 3, 4, 5, 6, more than 7?*

Given that the average equals two, we can say that $\lambda = \mu = \sigma^2 = 2$. Substituting the values $\mu = 2$ and $e = 2.71828$ in Equation 9.20, the probabilities are computed below for the values of x noted in Example 9.17.¹⁷

$$P(x = 0) = \frac{e^{-\mu} \mu^x}{x!} = \frac{(2.71828)^{-2} (2)^0}{0!} = .1353$$

This result tells us that the likelihood of zero traffic accidents occurring is .1353.

$$P(x = 1) = \frac{e^{-\mu} \mu^x}{x!} = \frac{(2.71828)^{-2} (2)^1}{1!} = .2707$$

This result tells us that the likelihood of one traffic accident occurring is .2707.

$$P(x = 2) = \frac{e^{-\mu} \mu^x}{x!} = \frac{(2.71828)^{-2} (2)^2}{2!} = .2707$$

This result tells us that the likelihood of two traffic accidents occurring is .2707.

$$P(x = 3) = \frac{e^{-\mu} \mu^x}{x!} = \frac{(2.71828)^{-2} (2)^3}{3!} = .1804$$

This result tells us that the likelihood of three traffic accidents occurring is .1804.

$$P(x = 4) = \frac{e^{-\mu} \mu^x}{x!} = \frac{(2.71828)^{-2} (2)^4}{4!} = .0902$$

This result tells us that the likelihood of four traffic accidents occurring is .0902.

$$P(x = 5) = \frac{e^{-\mu} \mu^x}{x!} = \frac{(2.71828)^{-2} (2)^5}{5!} = .0361$$

This result tells us that the likelihood of five traffic accidents occurring is .0361.

$$P(x = 6) = \frac{e^{-\mu} \mu^x}{x!} = \frac{(2.71828)^{-2} (2)^6}{6!} = .0120$$

This result tells us that the likelihood of six traffic accidents occurring is .0120.

The likelihood of seven or more accidents occurring is the sum of the probabilities for zero through six accidents (which is .9954) subtracted from 1. Thus, the likelihood of seven or more accidents occurring is $1 - .9954 = .0046$.

Under certain conditions the Poisson distribution can be employed to approximate the binomial distribution. When the latter is done it can facilitate the often tedious computations that are involved in determining binomial probabilities. The optimal conditions for approximating the binomial distribution with the Poisson distribution are when n is large and the value of π_1 is very small. Under the latter conditions the value of π_2 will be very close to 1, since $1 - \pi_1 = \pi_2$. In such a case if we set the value of π_2 equal to 1, Equation 9.2 (the equation for computing the standard deviation of a binomially distributed variable) reduces to $\sigma = \sqrt{n\pi_1\pi_2} = \sqrt{n\pi_1}$. If the latter is true, $\sigma^2 = n\pi_1$. Since the expected value of a binomially distributed variable is $\mu = n\pi_1$, under these conditions μ and σ^2 are identical, which is the case with a variable that conforms to a Poisson distribution. Thus, both μ and σ^2 may be represented by the parameter λ .

Consequently, we can say that when n is large and π_1 is very small, the relationship noted below is true (the notation \approx means approximately). The left side of the relationship is Equation 9.3 (the equation for computing the likelihood of a specific value of x for a binomially distributed variable), and the right side of the relationship is Equation 9.20 (the equation for computing the likelihood of a specific value of x for a variable that has a Poisson distribution).

$$\binom{n}{x} (\pi_1)^x (\pi_2)^{(n-x)} \approx \frac{e^{-\mu} \mu^x}{x!}$$

To illustrate the Poisson approximation of the binomial distribution, consider Example 9.18.

Example 9.18 Assume that there is a .03 probability of a specific microorganism growing in a culture. What is the likelihood that in a batch of 200 cultures five of the cultures will contain the microorganism?

Employing Equation 9.3, we compute the binomial probability for $n = 200$, $x = 5$, $\pi_1 = .03$, and $\pi_2 = .97$. The obtained value is $p = .1622$, which is the likelihood that in a batch of 200 cultures five will contain the microorganism.

$$P(x = 5) = \binom{n}{x} (\pi_1)^x (\pi_2)^{(n-x)} = \binom{200}{5} (.03)^5 (.97)^{195} = .1622$$

The Poisson estimate of the binomial probability is determined as follows. First, employing Equation 9.1 we compute the expected value μ , which is $\mu = 6$. We then employ the latter value along with $x = 5$ in Equation 9.20, and compute the probability .1606, which is the likelihood that in a batch of 200 cultures five will contain the microorganism. Note that the value $p = .1606$ is very close to the exact binomial probability of $p = .1622$.

$$\mu = \lambda = n\pi_1 = (200)(.03) = 6$$

$$P(x = 5) = \frac{e^{-\mu} \mu^x}{x!} = \frac{(2.71828)^{-6} (6)^5}{5!} = .1606$$

Sources are not in agreement with respect to what values of n and π_1 are appropriate for employing the Poisson approximation of the binomial distribution. Hogg and Tanis (1997) recommend the approximation if $n \geq 20$ and $\pi_1 \leq .05$, or if $n \geq 100$ and $\pi_1 \leq .10$. Daniel and Terrell (1995) concur with the latter, and state the approximation is usually very good when $n \geq 100$ and $n\pi_1 \leq 10$. Rosner (1995) states the more conservative criterion that $n \geq 100$ and $\pi_1 \leq .01$.

Evaluating goodness-of-fit for a Poisson distribution There may be occasions when a researcher wants to evaluate the hypothesis that a set of data is derived from a Poisson distribution. Example 9.19, which is an extension of Example 9.17, will be employed to demonstrate how the latter hypothesis can be evaluated with the **chi-square goodness-of-fit test**.

Example 9.19 *The traffic bureau of a Midwestern city determines that the average number of accidents per day is 2. During a 300-day period the following number of accidents are recorded per day: a) 30 days 0 accidents occur; b) 90 days there is 1 accident; c) 89 days there are 2 accidents; d) 53 days there are 3 accidents; e) 30 days there are 4 accidents; f) 6 days there are 5 accidents; g) 2 days there are 6 accidents; and h) 7 or more accidents do not occur on any day during the 300 day period. Is the distribution of the data consistent with a Poisson distribution?*

The null and alternative hypotheses that are evaluated with the **chi-square goodness-of-fit test** in reference to Example 9.19 can either be stated in the form as presented in Section III of the latter test (i.e., $H_0: o_i = e_i$ for all cells; $H_1: o_i \neq e_i$ for at least one cell), or as follows.

Null hypothesis H_0 : The sample is derived from a population with a Poisson distribution.

Alternative hypothesis H_1 : The sample is not derived from a population with a Poisson distribution. This is a **nondirectional alternative hypothesis**.

The analysis of Example 9.19 with the **chi-square goodness-of-fit test** is summarized in Table 9.7. The latter table is comprised of $k = 7$ cells/categories, with each cell corresponding to a given number of accidents per day. The second column of the table contains the observed

frequencies for the specified number of accidents. The expected frequency in Column 3 for each cell was obtained by employing Equation 8.1. Specifically the value 300, which represents the total number of days, is multiplied by the appropriate Poisson probability for a given number of accidents (which was previously computed in Example 9.17). The latter Poisson probabilities are as follows: $x = 0$ ($p = .1353$); $x = 1$ ($p = .2707$); $x = 2$ ($p = .2707$); $x = 3$ ($p = .1804$); $x = 4$ ($p = .0902$); $x = 5$ ($p = .0361$), and $x \geq 6$ ($p = .0120 + .0046 = .0166$). To illustrate the computation of an expected frequency, the value 40.59 is obtained for Row 1 (0 accidents) as follows: $E_i = (300)(.1353) = 40.59$.

Table 9.7 Chi-Square Summary Table for Example 9.19 (Poisson Analysis)

Cell/ Number of Accidents	O_i	E_i	$(O_i - E_i)$	$(O_i - E_i)^2$	$\frac{(O_i - E_i)^2}{E_i}$
0	30	40.59	-10.59	112.15	2.76
1	90	81.21	8.79	77.26	.95
2	89	81.21	7.79	60.68	.74
3	53	54.12	-1.12	1.25	.02
4	30	27.06	2.94	8.64	.32
5	6	10.83	-4.83	23.33	2.15
6 or more	2	4.98	-2.98	8.88	1.78
$\Sigma O_i = 300$		$\Sigma E_i = 300$	$\Sigma(O_i - E_i) = 0$		$\chi^2 = 8.72$

Employing Equation 8.2, the value $\chi^2 = 8.72$ is computed for Example 9.19. Since there are $k = 7$ cells and no parameters are estimated (i.e., $w = 0$), employing Equation 8.7, the degrees of freedom for the analysis are $df = 7 - 1 - 0 = 6$. Employing Table A4, we determine that for $df = 6$ the tabled critical .05 and .01 values are $\chi_{.05}^2 = 12.59$ and $\chi_{.01}^2 = 16.81$. Since the computed value $\chi^2 = 8.72$ is less than both of the aforementioned values, the null hypothesis cannot be rejected. Thus, the analysis does not indicate that the data deviate significantly from a Poisson distribution.

It should be noted that if, instead of stipulating the value $\mu = 2$ to represent the mean number of accidents, we computed the mean number of accidents from the sample data, the value of df is reduced by 1 (i.e., $df = 7 - 1 - 1 = 5$). The latter is the case since an additional degree of freedom must be subtracted for any parameter that is estimated. In point of fact, in Example 9.19 the sample data yield an average number of accidents equal to $\bar{X} = 1.96$. The latter value is obtained as follows: a) In each row of Table 9.7, multiply the value for the number of accidents in Column 1 by the observed frequency for that number of accidents in Column 2 (multiply 6 by 2 in the last row, since on the two days recorded there were six accidents); and b) Sum the eight products obtained in a). The latter sum will equal the total number of accidents (which comes out to 589), and if that value is divided by the total number of days (300) it yields the value $\bar{X} = 1.96$. The latter value would represent the best estimate of the population mean. Since the latter value is almost equal to $\mu = 2$ employed in the analysis, it would not result in a different conclusion.

It was noted earlier that when n is large and the value of π_1 is very small, the Poisson distribution provides a good approximation for the binomial distribution. In point of fact, the latter conditions apply to Example 9.19. If Example 9.19 is conceptualized within the framework of a binomial model, $n = 300$ and $\pi_1 = .0067$. Within the binomial model there are 300 trials and, on each trial, there are two possible outcomes, **accident** versus **no accident**. The value of π_1 can be computed through use of Equation 9.1 as follows: a) Transpose the terms in

the latter equation to solve for π_1 ; b) Since we know the mean of the distribution is $\mu = 2$ and $n = 300$, we obtain $\pi_1 = \mu/n = 2/300 = .0067$.

In point of fact, if the **chi-square goodness-of-fit test** is employed to evaluate the data for Example 9.19 for goodness-of-fit for a binomial distribution, the null hypothesis (which states that the data are derived from a binomial distribution) is supported. Table 9.8 summarizes the analysis. The following binomial probabilities are multiplied by 300 to get the expected frequency for each row of the table: $x = 0$ ($p = .1331$); $x = 1$ ($p = .2693$); $x = 2$ ($p = .2722$); $x = 3$ ($p = .1821$); $x = 4$ ($p = .0904$); $x = 5$ ($p = .0369$); and $x \geq 6$ ($p = .0161$). The latter probabilities were obtained through use of Equation 9.3 using the values $n = 300$, $\pi_1 = .0067$, $\pi_2 = .9933$, and the designated value of x . Note that the binomial probabilities are almost identical to the Poisson probabilities for the corresponding value of x .

Table 9.8 Chi-Square Summary Table for Example 9.19 (Binomial Analysis)

Cell/ Number of Accidents	O_i	E_i	$(O_i - E_i)$	$(O_i - E_i)^2$	$\frac{(O_i - E_i)^2}{E_i}$
0	30	39.93	-9.93	98.60	2.47
1	90	80.79	9.21	84.82	1.05
2	89	81.66	7.34	53.88	.66
3	53	54.63	-1.63	2.66	.05
4	30	27.12	2.88	8.29	.31
5	6	11.07	-5.07	25.70	2.32
6 or more	2	4.83	-2.83	8.01	1.66
$\Sigma O_i = 300$ $\Sigma E_i = 300$ $\Sigma(O_i - E_i) = 0$			$\chi^2 = 8.52$		

Employing Equation 8.2, the value $\chi^2 = 8.52$ is computed (which is almost identical to $\chi^2 = 8.72$ computed earlier for goodness-of-fit for a Poisson distribution). Since $df = 7 - 1 = 6$, employing Table A4, we determine that the tabled critical .05 and .01 values are $\chi^2_{.05} = 12.59$ and $\chi^2_{.01} = 16.81$. Since the computed value $\chi^2 = 8.52$ is less than both of the aforementioned values, the null hypothesis cannot be rejected. Thus, the analysis does not indicate that the data deviate significantly from a binomial distribution. The above example illustrates the fact that there are circumstances when a Poisson distribution and binomial distribution will be so similar to one another, that a goodness-of-fit test will not be able to clearly discriminate between the two distributions.

Zar (1999) describes additional analytical procedures that can be employed for the Poisson distribution, including computation of a confidence interval and a test of significance comparing two Poisson counts.

5. The matching distribution The **matching distribution** is a discrete probability distribution that can be employed to evaluate certain experimental situations. In order to describe the model for the matching distribution, let us assume that we have two identical decks of cards with n_1 cards in Deck 1 and n_2 cards in Deck 2, with $n_1 = n_2$. If we conduct an experiment that is comprised of n trials, and on each trial we randomly select one card from Deck 1 and one card from Deck 2, the probability of obtaining x matches between cards in the two decks is defined by Equation 9.21. Note that the terms enclosed in the brackets of Equation 9.21 constitute a series (which is a sequence of numbers that are added to and/or subtracted from one another).

(Equation 9.21)

$$P(x) = \frac{1}{x!} \left[\frac{1}{0!} - \frac{1}{1!} + \frac{1}{2!} - \frac{1}{3!} \dots \pm \frac{1}{(n-x)!} \right]$$

Example 9.20 will be used to illustrate how Equation 9.21 is employed to compute probabilities for the matching distribution.

Example 9.20 *A subject claims that he has extrasensory ability. To test the subject, the following five playing cards are randomly arranged face down on a table: Ace of spades; King of spades; Queen of spades; Jack of spades; Ten of spades. The subject is given a set of five cards with identical face values as those on the table, and told to place each of the cards he is holding on top of the corresponding card on the table. Is the subject's performance statistically significant at the .05 level if he matches two of the five cards correctly?*

In this experiment there are $n = 5$ trials, and we want to determine the probability of obtaining two or more matches. The null hypothesis to be evaluated is that the subject will perform within chance expectation (or to say it another way, the performance of the subject will not suggest extrasensory ability). The alternative hypothesis that will be evaluated is the directional/one-tailed alternative hypothesis that states the subject will perform at an above chance level (or to say it another way, the performance of the subject suggests extrasensory ability).

Equation 9.21 is employed below to compute the probability of obtaining $x = 0$, $x = 1$, $x = 3$, and $x = 5$ matches. Note that a subject cannot obtain 4 matches without obtaining 5 matches, since if there are $(n - 1)$ matches there must be n matches. The probabilities for all values of x sum to 1 (there is a slight discrepancy due to rounding off error).

$$P(x = 0) = \frac{1}{0!} \left[\frac{1}{0!} - \frac{1}{1!} + \frac{1}{2!} - \frac{1}{3!} + \frac{1}{4!} - \frac{1}{5!} \right] = .3664$$

This result tells us that the likelihood of a subject obtaining 0 matches is .3664.

$$P(x = 1) = \frac{1}{1!} \left[\frac{1}{0!} - \frac{1}{1!} + \frac{1}{2!} - \frac{1}{3!} + \frac{1}{4!} \right] = .3747$$

This result tell us that the likelihood of a subject obtaining 1 match is .3747.

$$P(x = 2) = \frac{1}{2!} \left[\frac{1}{0!} - \frac{1}{1!} + \frac{1}{2!} - \frac{1}{3!} \right] = .1665$$

This result tells us that the likelihood of a subject obtaining 2 matches is .1665.

$$P(x = 3) = \frac{1}{3!} \left[\frac{1}{0!} - \frac{1}{1!} + \frac{1}{2!} \right] = .0835$$

This result tells us that the likelihood of a subject obtaining 3 matches is .0835.

$$P(x = 4) = \frac{1}{4!} \left[\frac{1}{0!} - \frac{1}{1!} \right] = 0$$

This result tells us that the likelihood of a subject obtaining 4 matches is 0, since there cannot be 4 matches without 5 matches.

$$P(x = 5) = \frac{1}{5!} \left[\frac{1}{0!} \right] = .0083$$

This result tells us that the likelihood of a subject obtaining 5 matches is .0083.

To evaluate the subject's score of $x = 2$ matches, we have to determine the probability of obtaining two or more matches (i.e., $p(x \geq 2)$) when $n = 5$. The latter value is computed by adding the probabilities for 2, 3, and 5 matches computed above, since all of those values are equal to or greater than a score of 2 matches. Thus, $.1665 + .0835 + .0083 = .2583$. Since the obtained value $p = .2583$ is greater than the value $\alpha = .05$, we retain the null hypothesis. Thus, we cannot conclude that the subject exhibits evidence of extrasensory ability.

It turns out that the probabilities computed for the matching distribution are quite close to the probabilities that will result if the problem under discussion is reconceptualized within the framework of the **sampling with replacement model**. If the latter model is used, the appropriate distribution to employ to compute probabilities for the number of matches is the binomial distribution. To illustrate the use of the sampling with replacement model, let us assume that after the five test cards are placed face down on the table, the subject is told to randomly select one card from his own identical deck of five cards, and see if it matches the first card that is face down on the table. The subject then puts the card he selected from his own five card deck back into his deck, and randomly selects a second card and sees if it matches the second card that is face down on the table. The subject then puts the card he selected from his own five card deck back into his deck and continues the same process until he has attempted to randomly match a card from his complete five card deck with each of the five cards that are face down on the table. As described, this variant of the experiment involves $n = 5$ trials, and on any given trial there is a one in five chance of the subject being correct. Thus, we are dealing with a binomially distributed variable, where $n = 5$, $\pi_1 = 1/5 = .2$, and $\pi_2 = 4/5 = .8$. To determine the probability of obtaining 0, 1, 2, 3, 4, or 5 matches, we employ the section in **Table A6** for $n = 5$ and $\pi_1 = .2$. (Note that when the sampling with replacement model is employed, it is possible to obtain 4 matches.) The binomial probabilities obtained from **Table A6** are as follows: $x = 0$ ($p = .3277$); $x = 1$ ($p = .4096$); $x = 2$ ($p = .2048$); $x = 3$ ($p = .0512$); $x = 4$ ($p = .0064$); $x = 5$ ($p = .0003$). Note that the latter values are reasonably close to the probabilities for the matching distribution that were computed previously for the original problem. A more detailed discussion of the matching distribution can be found in Feller (1968).

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Endnotes

1. a) The binomial distribution is based on a process developed by the Swiss mathematician James Bernoulli (1654-1705). Each of the trials in an experiment involving a binomially distributed variable is often referred to as a **Bernoulli trial**. The conditions for Bernoulli trials are met when, in a set of repeated independent trials, on each trial there are only two possible outcomes, and the probability for each of the outcomes remains unchanged on every trial; b) The binomial model assumes **sampling with replacement**. To understand the latter term, imagine an urn that contains a large number of red balls and white balls. In each of n trials one ball is randomly selected from the urn. In the **sampling with replacement model**, after a ball is selected it is put back in the urn, thus insuring that the probability of drawing a red or white ball will remain the same on every trial. On the other hand, in the **sampling without replacement model**, the ball that is selected is not put back in the urn after each trial. Because of the latter, in the sampling without replacement model the probability of selecting a red ball versus a white ball will change from trial to trial, and on any trial the value of the probabilities will be a function of the number of balls of each color that remain in the urn. The binomial model assumes sampling with replacement, since on each trial the likelihood that an observation will fall in Category 1 will always equal π_1 , and the likelihood that an observation will fall in Category 2 will always equal π_2 . The classic situation for which the binomial model is employed is the process of flipping a fair coin. In the coin flipping situation, on each trial the likelihood of obtaining **Heads** is $\pi_1 = .5$, and the likelihood of obtaining **Tails** is $\pi_2 = .5$. The process of flipping a coin can be viewed within the framework of sampling with replacement, since it can be conceptualized as selecting from a large urn that is filled with the same number of **Heads** and **Tails** on every trial. In other words, it's as if after each trial the alternative that was selected on that

trial is thrown back into the urn, so that the likelihood of obtaining **Heads** or **Tails** will remain unchanged from trial to trial. In Section IX (the **Addendum**) the **hypergeometric distribution** (another discrete probability distribution) is described, which is based upon the sampling without replacement model; c) The binomial distribution is actually a special case of the **multinomial distribution**. In the latter distribution, each of n independent observations can be classified in one of k mutually exclusive categories, where k can be any integer value equal to or greater than two. The multinomial distribution is described in detail in Section IX (The **Addendum**).

2. The reader should take note of the fact that most sources employ the notations p and q to represent the population proportions π_1 and π_2 . Because of this, the equations for the mean and standard deviation of a binomially distributed variable are written as follows: $\mu = np$ and $\sigma = \sqrt{npq}$. The use of the notations π_1 and π_2 in this book for the population proportions is predicated on the fact that throughout the book Greek letters are employed to represent population parameters.
3. Using the format employed for stating the null hypothesis and the nondirectional alternative hypothesis for the **chi-square goodness-of-fit test**, H_0 and H_1 can also be stated as follows for the **binomial sign test for a single sample**: $H_0: o_i = e_i$ for both cells; $H_1: o_i \neq e_i$ for both cells. Thus, the null hypothesis states that in the underlying population the sample represents, for both cells/categories, the observed frequency of a cell is equal to the expected frequency of the cell. The alternative hypothesis states that in the underlying population the sample represents, for both cells/categories, the observed frequency of a cell is not equal to the expected frequency of the cell.
4. The question can also be stated as follows: If $n = 10$ and $\pi_1 = \pi_2 = .5$, what is the probability of 2 or less observations in one of the two categories? When $\pi_1 = \pi_2 = .5$, the probability of two or less observations in Category 2 will equal the probability of eight or more observations in Category 1 (or vice versa). When, however, $\pi_1 \neq \pi_2$, the probability of 2 or less observations in Category 2 will not equal the probability of 8 or more observations in Category 1.
5. The number of **combinations of n things taken x at a time** represents the number of different ways that n objects can be arranged x at a time without regard to order. For instance, if one wants to determine the number of ways that 3 objects (which we will designate A, B, and C) can be arranged 2 at a time without regard to order, the following 3 outcomes are possible: 1) An A and a B (which can result from either the sequence AB or BA); 2) An A and a C (which can result from either the sequence AC or CA); or 3) A B and a C (which can result from the sequence BC or CB). Thus, there are 3 combinations of ABC taken 2 at a time. This is confirmed below through use of Equation 9.4.

$$\binom{3}{2} = \frac{3!}{2! (3 - 2)!} = \frac{3!}{2! 1!} = 3$$

To extend the concept of combinations to a coin tossing situation, let us assume that one wants to determine the exact number of ways 2 **Heads** can be obtained if a coin is tossed 3 times. If a fair coin is tossed 3 times, any one of the following 8 sequences of **Heads** (H) and **Tails** (T) is equally likely to occur: HHH, HHT, THH, HTH, THT, HTT, TTH, TTT. Of the 8 possible sequences, only the following 3 sequences involve 2 **Heads**

and 1 **Tails**: *HHT, THH, HTH*. The latter 3 arrangements represent the combination of 3 things taken 2 at a time. This can be confirmed by $\binom{3}{2} = \frac{3!}{2! 1!} = 3$.

When the order of the arrangements is of interest, one can compute the number of **permutations of n things taken x at a time**. The latter is represented by the notation P_x^n , where $P_x^n = n!/(n - x)!$. Thus, if one is interested in the order when the events *A*, *B*, and *C* are taken 2 at a time, the following number of permutations are computed: $P_2^3 = 3!/(3 - 2)! = 3!/1!$. The 6 possible arrangements taking order into account are *AB, BA, AC, CA, BC, and CB*.

Although based on the definition of a permutation that has been presented above, one might conclude that the three combinations *HHT, THH, HTH* take order into account, and thus represent permutations, they can be conceptualized as combinations if one views the binomial model as follows: Within each of the three combinations *HHT, THH, HTH*, the 2 **Heads** are **distinguishable** from one another, insofar as each of the **Heads** can be assigned a subscript to designate it as distinct from the other **Heads**. To illustrate, within the combination *HHT*, H_1 and H_2 can be employed to distinguish the two **Heads** from one another. If we imagine that the two **Heads** are randomly selected from an urn, and one **Heads** is assigned the label H_1 , and the other **Heads** is assigned the label H_2 , the following two permutations are possible: H_1H_2T, H_2H_1T . Thus, the arrangement *HHT* is a combination that summarizes the two distinct permutations H_1H_2T, H_2H_1T . Based on what has been said, it follows that the following 6 permutations comprise the 3 combinations *HHT, THH*, and *HTH*: $H_1H_2T, H_2H_1T, TH_1H_2, TH_2H_1, H_1TH_2, H_2TH_1$. In point of fact, many sources (e.g., Marascuilo and McSweeney (1977, pp. 12–13)) describe the value computed for the binomial coefficient as a permutation, since it can be viewed as representing a value based on two sets of different but identical objects.

6. The application of Equation 9.3 to every possible value of x (i.e., in the case of Examples 9.1 and 9.2, the integer values 0 through 10) will yield a probability for every value of x . The sum of these probabilities will always equal 1. The algebraic expression which summarizes the summation of the probability values for all possible values of x is referred to as the **binomial expansion**, summarized by Equation 9.5, which is equivalent to the general equation $(\pi_1 + \pi_2)^n$ (or $(p + q)^n$ when p and q are employed in lieu of π_1 and π_2). Thus:

$$\sum_{r=x}^n \binom{n}{x} (\pi_1)^x (\pi_2)^{(n-x)} = (\pi_1 + \pi_2)^n$$

To illustrate, if $n = 3$, $\pi_1 = .5$, and $\pi_2 = .5$, the binomial expansion is as follows.

$$\begin{aligned} (\pi_1 + \pi_2)^3 &= (\pi_1)^3 + 3(\pi_1)^2(\pi_2) + 3(\pi_1)(\pi_2)^2 + (\pi_2)^3 \\ &= (.5)^3 + 3(.5)^2(.5) + 3(.5)(.5)^2 + (.5)^3 \end{aligned}$$

Each of the four terms that comprise the above noted binomial expansion can be computed with Equation 9.3 as noted below. The computed probabilities .125, .375, .375, and .125 are respectively the likelihood of obtaining 3, 2, 1, and 0 outcomes of π_1 if $n = 3$ and $\pi_1 = .5$.

$$\textbf{Term 1 } (P(3/3)) = (\pi_1)^3 = \binom{3}{3} (.5)^3 (.5)^0 = .125$$

$$\text{Term 2 } (P(2/3)) = 3(\pi_1)^2(\pi_2) = \binom{3}{2}(.5)^2(.5) = .375$$

$$\text{Term 3 } (P(1/3)) = 3(\pi_1)(\pi_2)^2 = \binom{3}{1}(.5)(.5)^2 = .375$$

$$\text{Term 4 } (P(0/3)) = (\pi_2)^3 = \binom{3}{0}(.5)^0(.5)^3 = .125$$

7. If $\pi = .5$ and one wants to determine the likelihood of x being equal to or less than a specific value, one can employ the cumulative probability listed for the value $(n - x)$. Thus, if $x = 2$, the cumulative probability for $x = 8$ (which is .0547) is employed since $n - x = 10 - 2 = 8$. The value .0547 indicates the likelihood of obtaining 2 or less observations in a cell. This procedure can only be used when $\pi_1 = .5$, since, when the latter is true, the binomial distribution is symmetrical.
8. If in using [Tables A6](#) and [A7](#) the value of π_2 is employed to represent π in place of π_1 , and the number of observations in Category 2 is employed to represent the value of x instead of the number of observations in Category 1, then the following are true: a) In [Table A6](#) (if all values of π within the range from 0 to 1 are listed) the probability associated with the cell that is the intersection of the values $\pi = \pi_2$ and x (where x represents the number of observations in Category 2) will be equivalent to the probability associated with the cell that is the intersection of $\pi = \pi_1$ and x (where x represents the number of observations in Category 1); and b) In [Table A7](#) (if all values of π within the range from 0 to 1 are listed) for $\pi = \pi_2$, the probability of obtaining x or fewer observations (where x represents the number of observations in Category 2) will be equivalent to for $\pi = \pi_1$, the probability of obtaining x or more observations (where x represents the number of observations in Category 1). Thus if $\pi_1 = .7$, $\pi_2 = .3$, and $n = 10$ and there are 9 observations in Category 1 and 1 observation in Category 2, the following are true: a) The probability in [Table A6](#) for $\pi = \pi_2 = .3$ and $x = 1$ will be equivalent to the probability for $\pi = \pi_1 = .7$ and $x = 9$; and b) In [Table A7](#) if $\pi = \pi_2 = .3$, the probability of obtaining 1 or fewer observations will be equivalent to the probability of obtaining 9 or more observations if $\pi = \pi_1 = .7$.
A modified protocol for employing [Table A7](#) when a more extreme value is defined as any value that is larger than the smaller of the two observed frequencies, or smaller than the larger of the two observed frequencies is described in Section VIII in reference to Example 9.9.
9. It will also answer at the same time whether $p_2 = 2/10 = .2$, the observed proportion of cases for Category 2, deviates significantly from $\pi_2 = .5$.
10. Since like the normal distribution the binomial distribution is a two-tailed distribution, the same basic protocol is employed in interpreting nondirectional (i.e., two-tailed) and directional (one-tailed) probabilities. Thus, in interpreting binomial probabilities one can conceptualize a distribution that is similar in shape to the normal distribution, and substitute the appropriate binomial probabilities in the distribution.
11. In Example 9.4 many researchers might prefer to employ the directional alternative

hypothesis $H_1: \pi_1 < .5$, since the senator will only change her vote if the observed proportion in the sample is less than .5. In the same respect, in Example 9.5 one might employ the directional alternative hypothesis $H_1: \pi_1 > .5$, since most people would only interpret above chance performance as indicative of extrasensory perception.

12. Equation 9.7 can also be expressed in the form $z = (X - \mu)/\sigma$. Note that the latter equation is identical to Equation I.27, the equation for computing a standard deviation score for a normally distributed variable. The difference between Equations 9.7 and I.27 is that Equation 9.7 computes a normal approximation for a binomially distributed variable, whereas Equation I.27 computes an exact value for a normally distributed variable.
13. The reader may be interested in knowing that in extrasensory perception (ESP) research, evidence of ESP is not necessarily limited to above chance performance. A person who consistently scores significantly below chance or only does so under certain conditions (such as being tested by an extremely skeptical and/or hostile experimenter) may also be used to support the existence of ESP. Thus, in Example 9.6, the subject who obtains a score of 80 (which is significantly below the expected value $\mu = 100$) represents someone whose poor performance (referred to as **psi missing**) might be used to suggest the presence of extrasensory processes.
14. When the **binomial sign test for a single sample** is employed to evaluate a hypothesis regarding a population median, it is categorized by some sources as a test of ordinal data (rather than as a test of categorical/nominal data), since, when data are categorized with respect to the median, it implies ordering of the data within two categories (i.e., **above the median** versus **below the median**).
15. a) In the discussion of the **Wilcoxon signed-ranks test**, it is noted that the latter test is not recommended if there is reason to believe that the underlying population distribution is asymmetrical. Thus, if there is reason to believe that blood cholesterol levels are not distributed symmetrically in the population, the **binomial sign test for a single sample** would be recommended in lieu of the **Wilcoxon signed-ranks test**; b) Marascuilo and McSweeney (1977) note that the **asymptotic relative efficiency** (discussed in Section VII of the **Wilcoxon signed-ranks test**) of the **binomial sign test for a single sample** is generally lower than that of the **Wilcoxon signed-ranks test**. If the underlying population distribution is normal, the asymptotic relative efficiency of the binomial sign test is .637, in contrast to an asymptotic relative efficiency of .955 for the **Wilcoxon signed-ranks test** (with both asymptotic relative efficiencies being in reference to the **single-sample t test**). When the underlying population distribution is not normal, in most cases, the asymptotic relative efficiency of the **Wilcoxon signed-ranks test** will be higher than the analogous value for the **binomial sign test**.
16. The reader should take note of the fact that the protocol in using **Table A7** to interpret a π_2 value that is less than .5 in reference to the value $\pi_2 = .1$ is different than the one described in the last paragraph of Section IV. The reason for this is that in Example 9.9 we are interested in (for $\pi_2 = .1$) the probability that the number of observations in Category 2 (**females**) are equal to or greater than 3 (which equals the probability that the number of observations in Category 1 (**males**) are equal to or less than 7 for $\pi_1 = .9$). The protocol presented in the last paragraph of Section IV in reference to the value $\pi_2 = .3$ describes the use of **Table A7** to determine the probability that the number of observations in Category

2 are equal to or less than 1 (which equals the probability that the number of observations in Category 1 are equal to or greater than 9 for $\pi_1 = .7$). Note that in Example 9.9 a more extreme score is defined as one that is larger than the lower of the two observed frequencies or smaller than the larger of the two observed frequencies. On the other hand, in the example in the last paragraph of Section IV a more extreme score is defined as one that is smaller than the lower of the two observed frequencies or larger than the higher of the two observed frequencies. The criteria for defining what constitutes an extreme score is directly related to the alternative hypothesis the researcher employs. If the alternative hypothesis is nondirectional, an extreme score can fall both above or below an observed frequency, whereas if a directional alternative hypothesis is employed, a more extreme score can only be in the direction indicated by the alternative hypothesis.

17. Endnote 5 in the **Introduction** states that the value e is the base of the natural system of logarithms. e , which equals 2.71828... , is an **irrational number** (i.e., a number that has a decimal notation that goes on forever without a repeating pattern of digits).

Test 10

The Single-Sample Runs Test (and Other Tests of Randomness)

(Nonparametric Test Employed with Categorical/Nominal Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test Is the distribution of a series of binary events in a population random?

Relevant background information on test By definition a **random series** is one for which no algorithm (i.e., set of rules) can be generated that will allow one to predict at above chance which of the k possible alternatives will occur on a given trial.¹ The **single-sample runs test** is one of a number of statistical procedures that have been developed for evaluating whether or not the distribution of a series of N numbers is **random**. The test evaluates the number of **runs** in a series in which, on each trial, the outcome must be one of $k = 2$ alternatives. Within the series, one of the alternatives occurs on n_1 trials and the other alternative occurs on n_2 trials. Thus, $n_1 + n_2 = N$. A **run** is a sequence within a series in which one of the k alternatives occurs on consecutive trials. On the trial prior to the first trial of a run (with the exception of Trial 1 in the series) and the trial following the last trial of a run (with the exception of the N^{th} trial in the series), the alternative that occurs will be different than the alternative that occurs during each of the trials of the run. The minimum length of a run is one trial, and the maximum length of a run is equal to N , the total number of trials in the series. To illustrate the computation of the length of a run, consider the three series noted in Figure 10.1. Each series is comprised of $N = 10$ trials. On each trial a coin is flipped and the outcome of **Heads (H)** or **Tails (T)** is recorded.

Trial	1	2	3	4	5	6	7	8	9	10
Series A:	H	H	T	H	H	T	T	T	H	T
Series B:	T	H	T	H	T	H	T	H	T	H
Series C:	H	H	H	H	H	H	H	H	H	H

Figure 10.1 Illustration of Runs

In **Series A** and **Series B** there are $n_1 = 5$ Heads and $n_2 = 5$ Tails. In **Series C** there are $n_1 = 10$ Heads and $n_2 = 0$ Tails.

In **Series A** there are six runs. Run 1 consists of Trials 1 and 2 (which are **Heads**). Run 2 consists of Trial 3 (which is **Tails**). Run 3 consists of Trials 4 and 5 (which are **Heads**). Run 4 consists of Trials 6–8 (which are **Tails**). Run 5 consists of Trial 9 (which is **Heads**). Run 6 consists of Trial 10 (which is **Tails**). This can be summarized visually by underlining all of the runs as noted below. Note that all the runs are comprised of sequences involving the same alternative. Thus: **H H** **T** **H H** **T T T** **H** **T**.

In **Series B** there are 10 runs. Each of the trials constitutes a separate run, since on each trial a different alternative occurs. Note that on each trial the alternative for that trial is preceded by

and followed by a different alternative. Thus: **T H T H T H T H T H**. As noted in the definition of a run, Trial 1 cannot be preceded by a different alternative, since it is the first trial, and Trial 10 cannot be followed by a different alternative, since it is the last trial.

In **Series C** there is one run. This is the case, since the same alternative occurs on each trial. Thus: **H H H H H H H H H H**.

Intuitively, one would expect that of the three series, **Series A** is most likely to conform to the definition of a random series. This is the case, since it is highly unlikely that a random series will exhibit a discernible pattern that will allow one to predict at above chance which of the alternatives will appear on a given trial. **Series B** and **C**, on the other hand, are characterized by patterns that will probably bias the guess of someone who is attempting to predict what the outcome will be if there is an eleventh trial. It is logical to expect that the strength of such a bias will be a direct function of the length of any series exhibiting a consistent pattern.²

The test statistic for the **single-sample runs test** is based on the assumption that the number of runs in a random series will be expected to fall within a certain range of values. Thus, if for a given series the number of runs is less than some minimum value or greater than some maximum value, it is likely that the series is not random. The determination of the minimum allowable number of runs and maximum allowable number of runs in a series of N trials takes into account the number of runs, as well as the frequency of occurrence of each of the two alternatives within the series.

It should be noted that although the **single-sample runs test** is most commonly employed with a binomially distributed variable for which $\pi_1 = \pi_2 = .5$ (as is the case for a coin toss), it is not required that the values π_1 and π_2 equal .5 in the underlying population. It is important to remember that the runs test does not evaluate a hypothesis regarding the values of π_1 and π_2 in the underlying population, nor does it make any assumption with regard to the latter values. The test statistic for the runs test is a function of the proportion of times each of the alternatives occurs in the sample data/series (i.e., $p_1 = n_1/N$ and $p_2 = n_2/N$). If the observed proportion for each of the alternatives is inconsistent with its actual proportion in the underlying population, the **single-sample runs test** is not designed to detect such a difference. Example 10.7 in Section VIII illustrates a situation in which the **single-sample runs test** is employed when it is known that $\pi_1 \neq \pi_2 \neq .5$.

II. Example

Example 10.1 *In a test of extrasensory ability, a coin is flipped 20 times by an experimenter. Prior to each flip of the coin the subject is required to guess whether it will come up Heads or Tails. After each trial the subject is told whether his guess is correct or incorrect. The actual outcomes for the 20 coin flips are listed below:*

H H H T T T H H T T H T H T H T T T H H

To rule out the possibility that the subject gained extraneous information as a result of a nonrandom pattern in the above series, the experimenter decides to evaluate it with respect to randomness. Does an analysis of the series suggest that it is nonrandom?

III. Null versus Alternative Hypotheses

Null hypothesis H_0 : The events in the underlying population represented by the sample series are distributed randomly.

Alternative hypothesis H_1 : The events in the underlying population represented by the sample series are distributed nonrandomly. (This is a **nondirectional alternative hypothesis** and it is evaluated with a **two-tailed test**.)

or

H_1 : The events in the underlying population represented by the sample series are distributed nonrandomly due to too few runs. (This is a **directional alternative hypothesis** and it is evaluated with a **one-tailed test**.)

or

H_1 : The events in the underlying population represented by the sample series are distributed nonrandomly due to too many runs. (This is a **directional alternative hypothesis** and it is evaluated with a **one-tailed test**.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis is rejected.

IV. Test Computations

In order to compute the test statistic for the **single-sample runs test**, one must determine the number of times each of the two alternatives appears in the series and the number of runs in the series. Thus, we determine that the series described in Example 10.1 is comprised of $n_1 = 10$ Heads and $n_2 = 10$ Tails. Note that $n_1 + n_2 = N = 20$. We also determine that there are $r = 11$ runs, which represents the test statistic for the **single-sample runs test**. Specifically as one moves from Trial 1 to Trial 20: **H H H** (Run 1); **T T T** (Run 2); **H H** (Run 3); **T T** (Run 4); **H** (Run 5); **T** (Run 6); **H** (Run 7); **T** (Run 8); **H** (Run 9); **T T T** (Run 10); and **H H** (Run 11). This can also be represented visually by underlining each of the runs. Thus:

H H H **T T T** **H H** **T T** **H** **T** **H** **T** **H** **T T T** **H H**

V. Interpretation of the Test Results

The computed value $r = 11$ is interpreted by employing **Table A8 (Table of Critical Values for the Single-Sample Runs Test)** in the **Appendix**. The critical values listed in **Table A8** only allow the null hypothesis to be evaluated at the .05 level if a two-tailed/nondirectional alternative hypothesis is employed, and at the .025 level if a one-tailed/directional alternative hypothesis is employed. No critical values are recorded in **Table A8** for the **single-sample runs test** for very small sample sizes, since the levels of significance employed in the table cannot be achieved for sample sizes below a specific minimum value. More extensive tables for the **single-sample runs test** which provide critical values for other levels of significance can be found in Swed and Eisenhart (1943) and Beyer (1968).³

Note that in **Table A8** the critical r values are listed in reference to the values of n_1 and n_2 , which represent the frequencies that each of the alternatives occurs in the series. Since in Example 10.1, $n_1 = 10$ and $n_2 = 10$, we locate the cell in **Table A8** that is the intersection of these two values. In the appropriate cell, the upper value identifies the **lower limit** for the value of r , whereas the lower value identifies the **upper limit** for the value of r . The following guidelines are employed in reference to the latter values.

a) If the nondirectional alternative hypothesis is employed, to reject the null hypothesis, the obtained value of r must be equal to or greater than the tabled critical upper limit at the

prespecified level of significance, or be equal to or less than the tabled critical lower limit at the prespecified level of significance.

b) If the directional alternative hypothesis predicting too few runs is employed, to reject the null hypothesis, the obtained value of r must be equal to or less than the tabled critical lower limit at the prespecified level of significance.

c) If the directional alternative hypothesis predicting too many runs is employed, to reject the null hypothesis, the obtained value of r must be equal to or greater than the tabled critical upper limit at the prespecified level of significance.⁴

Employing **Table A8**, we determine that for $n_1 = n_2 = 10$, the tabled critical lower and upper critical r values are $r = 6$ and $r = 16$. Thus, if the nondirectional alternative hypothesis is employed (with $\alpha = .05$), the obtained value of r will be significant if it is equal to or less than 6 or equal to or greater than 16. In other words, it will be significant if there are either 16 or more runs or 6 or less runs in the data. Since $r = 11$ falls inside this range, the nondirectional alternative hypothesis is not supported.

If the directional alternative hypothesis predicting too few runs is employed (with $\alpha = .025$), the obtained value of r will only be significant if it is equal to or less than 6. In other words, it will only be significant if there are 6 or less runs in the data. Since $r = 11$ is greater than 6, the directional alternative hypothesis predicting too few runs is not supported.

If the directional alternative hypothesis predicting too many runs is employed (with $\alpha = .025$), the obtained value of r will only be significant if it is equal to or greater than 16. In other words, it will only be significant if there are 16 or more runs in the data. Since $r = 11$ is less than 16, the directional alternative hypothesis predicting too many runs is not supported.

Our analysis indicates that regardless of which alternative hypothesis one employs, the null hypothesis cannot be rejected. Thus, the data do not allow the researcher to conclude that the series is nonrandom.

VI. Additional Analytical Procedures for the Single-Sample Runs Test and/or Related Tests

1. The normal approximation of the single-sample runs test for large sample sizes The normal distribution can be employed with a large sample size/series to approximate the exact distribution of the **single-sample runs test**. The large sample approximation is generally employed for sample sizes larger than those documented in **Table A8**. Equation 10.1 is employed for the normal approximation of the **single-sample runs test**.

$$z = \frac{r - u_r}{\sigma_r} = \frac{r - \left[\frac{2n_1 n_2}{n_1 + n_2} + 1 \right]}{\sqrt{\frac{2n_1 n_2 (2n_1 n_2 - n_1 - n_2)}{(n_1 + n_2)^2 (n_1 + n_2 - 1)}}} \quad (\text{Equation 10.1})$$

In the numerator of the above equation the term $[(2n_1 n_2)/(n_1 + n_2)] + 1$ represents the mean of the sampling distribution of runs in a random series in which there are N observations. The latter value may be summarized with the notation u_r . In other words, given $n_1 = 10$ and $n_2 = 10$, if in fact the distribution is random, the best estimate of the number of runs one can expect to observe is $\mu_r = 11$. The denominator in Equation 10.1 represents the expected standard deviation of the sampling distribution for the normal approximation of the test statistic. The latter value is summarized by the notation σ_r .

Employing Equation 10.1 with the data for Example 10.1, the value $z = 0$ is computed.

$$z = \frac{11 - \left[\frac{(2)(10)(10)}{10 + 10} + 1 \right]}{\sqrt{\frac{(2)(10)(10)[(2)(10)(10) - 10 - 10]}{(10 + 10)^2(10 + 10 - 1)}}} = \frac{0}{2.18} = 0$$

Since $\mu_r = 11$ and $\sigma_r = 2.18$, the result of the above analysis can also be summarized as follows: $z = (11 - 11)/2.18 = 0$.

The obtained value $z = 0$ is evaluated with **Table A1 (Table of the Normal Distribution)** in the **Appendix**. To be significant, the obtained absolute value of z must be equal to or greater than the tabled critical value at the prespecified level of significance. The tabled critical two-tailed .05 and .01 values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed .05 and .01 values are $z_{.05} = 1.65$ and $z_{.01} = 2.33$. The following guidelines are employed in evaluating the null hypothesis.

a) If the nondirectional alternative hypothesis is employed, to reject the null hypothesis, the obtained absolute value of z must be equal to or greater than the tabled critical two-tailed value at the prespecified level of significance. In Example 10.1 the nondirectional alternative hypothesis is not supported, since the obtained value $z = 0$ is less than both of the aforementioned tabled critical two-tailed values.

b) If the directional alternative hypothesis predicting too few runs is employed, to reject the null hypothesis, the following must be true: 1) The obtained value of z must be a negative number; and 2) The absolute value of z must be equal to or greater than the tabled critical one-tailed value at the prespecified level of significance. In Example 10.1 the directional alternative hypothesis predicting too few runs is not supported, since the obtained value $z = 0$ is not a negative number (as well as the fact that it is less than the tabled critical one-tailed values $z_{.05} = 1.65$ and $z_{.01} = 2.33$).

c) If the directional alternative hypothesis predicting too many runs is employed, to reject the null hypothesis, the following must be true: 1) The obtained value of z must be a positive number; and 2) The absolute value of z must be equal to or greater than the tabled critical one-tailed value at the prespecified level of significance. In Example 10.1 the directional alternative hypothesis predicting too many runs is not supported, since the obtained value $z = 0$ is not a positive number (as well as the fact that it is less than the tabled critical one-tailed values $z_{.05} = 1.65$ and $z_{.01} = 2.33$).

Thus, when the normal approximation is employed, as is the case when the critical values in **Table A8** are used, the null hypothesis cannot be rejected regardless of which alternative hypothesis is employed. Consequently, we cannot conclude that the series is not random.

2. The correction for continuity for the normal approximation of the single-sample runs test Although it is not described by most sources, Siegel and Castellan (1988) recommend that a correction for continuity be employed for the normal approximation of the **single-sample runs test**. Equation 10.2, which is the continuity-corrected equation, will always yield a smaller absolute z value than the value derived with Equation 10.1.⁵

$$z = \frac{|r - \mu_r| - .5}{\sigma_r} \quad (\text{Equation 10.2})$$

Employing Equation 10.2 with the data for Example 10.1, the value $z = -.23$ is computed.

$$z = \frac{|11 - 11| - .5}{2.18} = -.23$$

Since the absolute value $z = .23$ is lower than the tabled critical two-tailed value $z_{.05} = 1.96$ and the tabled critical one-tailed value $z_{.05} = 1.65$, the null hypothesis cannot be rejected, regardless of which alternative hypothesis is employed (which is also the case when the correction for continuity is not employed). Thus, we cannot conclude that the series is not random.

3. Extension of the runs test to data with more than two categories Wallis and Roberts (1956) and Zar (1999) note that Equations 10.3 and 10.4 can be employed for the **single-sample runs test** when the data fall into more than two categories. Equation 10.3 computes the mean of the sampling distribution (i.e., μ_r , the expected number of runs) and, Equation 10.4 computes the expected standard deviation of the sampling distribution (σ_r). When there are two categories, Equation 10.3 is equivalent to the term on the right side of the numerator of Equation 10.1 (i.e., u_r), and Equation 10.4 is equivalent to the denominator of Equation 10.1 (i.e., σ_r). The values computed for μ_r and σ_r are substituted in the normal approximation equation for the **single-sample runs test**—i.e., Equation 10.1 (the continuity-corrected version Equation 10.2 may also be employed). The computed value of z is interpreted in the same manner as when there are two categories.

$$\mu_r = \frac{N(N + 1) - \sum n_i^2}{N} \quad \text{(Equation 10.3)}$$

$$\sigma_r = \sqrt{\frac{\sum n_i^2 [\sum n_i^2 + N(N + 1)] - 2N \sum n_i^3 - N^3}{N^2(N - 1)}} \quad \text{(Equation 10.4)}$$

With respect to the notation employed in Equations 10.3 and 10.4, note that there will be k categories with the following number of trials/observations for each category: $n_1, n_2, n_3, \dots, n_k$. Since n_i represents the number of trials/observations for the i^{th} category, $N = \sum n_i$. The notation $\sum n_i^2$ and $\sum n_i^3$, respectively, indicate that the number of observations in each category are squared and cubed, and the latter values are summed.

To illustrate the **single-sample runs test** when there are more than two categories, assume we have a three-sided die that on each trial can come up as face value **A**, **B**, or **C**. Assume the pattern of results noted below is obtained.

A A B C C B A A B B C C A C B A A B B B

Each of the runs (which are comprised of one or more consecutive identical outcomes) is underlined, yielding a total of 12 runs. If we let n_1 represent the number of trials in which **A** appears, n_2 represent the number of trials in which **B** appears, and n_3 represent the number of trials in which **C** appears, then $n_1 = 7$, $n_2 = 8$, $n_3 = 5$, and $N = 20$. We can compute that $\sum n_i^2 = 7^2 + 8^2 + 5^2 = 138$ and $\sum n_i^3 = 7^3 + 8^3 + 5^3 = 980$. Substituting the appropriate values in Equations 10.3, 10.4, and 10.1, we compute the value $z = -1.06$.

$$\mu_r = \frac{20(20 + 1) - 138}{20} = 14.1$$

$$\sigma_r = \sqrt{\frac{138[138 + 20(20 + 1)] - (2)(20)(980) - (20)^3}{(20)^2(20 - 1)}} = 1.98$$

$$z = \frac{r - \mu_r}{\sigma_r} = \frac{12 - 14.1}{1.98} = -1.06$$

The correction for continuity can be employed by subtracting .5 from the absolute value in the numerator of Equation 10.1. When the correction for continuity is employed, $z = (|12 - 14.1| - .5)/1.98 = -.81$. Since the absolute values $z = 1.06$ and $z = .81$ are lower than the tabled critical two-tailed value $z_{.05} = 1.96$ and the tabled critical one-tailed value $z_{.05} = 1.65$, the null hypothesis cannot be rejected, regardless of which alternative hypothesis is employed. Thus, we cannot conclude that the series is not random. The negative sign for z just indicates that the observed number of runs was less than the expected value.

The reader should note that **Table A8** cannot be employed to evaluate the results of the analysis described in this section, since the latter table is only designed for use with two categories. Zar (1999) notes that O'Brien (1976) and O'Brien and Dyck (1985) have developed a more powerful version of the runs test that can be employed when there are more than two categories. Other tests of randomness that can be employed when there are more than two categories are discussed in Section IX (the **Addendum**).

4. Test 10a: The runs test for serial randomness A variant of the **single-sample runs test** described in this section is the **runs test for serial randomness** (also referred to as the **up-down runs test**). The use of the term **serial** refers to the analysis of the sequence of events in a series. Attributed to Wallis and Moore (1941), the **runs test for serial randomness** (which is also discussed in Schmidt and Taylor (1970) and Zar (1999)) is employed when the data being evaluated are in a quantitative rather than a categorical format. In such a case a researcher might want to determine if the shifts in the direction (i.e., up or down) of a sequence of scores is in a random order. Within the framework of this test, each shift in direction represents the beginning of a new run. The total number of runs is the total number of directional shifts in a set of data. To illustrate, consider the following set of ten scores:

+ - + + - - - - +
2, 3, 1, 6, 7, 4, 3, 2, 1, 7,

Note that a plus sign (+) is recorded at the upper right of a score if the score that follows it is larger, and a minus sign (-) is recorded if the score that follows it is smaller. Runs are determined as they were with the **single-sample runs test**. Thus, each string of plus signs or minus signs constitutes a run. In the above example there are five runs. The first two runs are comprised of a plus and a minus sign (+ -), followed by a run comprised of two plus signs (+ +), followed by a run comprised of four minus signs (- - - -), followed by a run comprised of a plus sign (+). Note that the total number of plus and minus signs is one less than the total number of scores.

The null hypothesis evaluated by the **runs test for serial randomness** is that in a set of data the distribution of successive changes in direction (i.e., runs) is random. The nondirectional alternative hypothesis is that in a set of data the distribution of successive changes in direction (runs) is not random. The alternative hypothesis can also be stated directionally. Specifically, one can predict a nonrandom pattern involving an excessive number of shifts in direction (resulting in a higher than expected number of runs), or a nonrandom pattern involving very few shifts in direction (resulting in a lower than expected number of runs).

Zar (1999) has prepared a table of exact probabilities for the **runs test for serial randomness** when $N < 50$. However, for large sample sizes (generally 50 or more trials/observations), Equation 10.7 can be employed to evaluate the results of the test. Note that although the latter equation has the same structure as the normal approximation equation for the **single-sample runs test**, in the case of the **runs test for serial randomness** Equations 10.5 and 10.6 are employed to compute the values of the expected number of runs (μ_r) and the expected standard deviation (σ_r). The computed value of z is interpreted in the same manner as it is for the **single-sample runs test**. As is the case with the latter test, it will require either a very large or very small number of runs to reject the null hypothesis, and thus conclude that the data indicate a lack of randomness.

$$\mu_r = \frac{2N - 1}{3} \quad (\text{Equation 10.5})$$

$$\sigma_r = \sqrt{\frac{16N - 29}{90}} \quad (\text{Equation 10.6})$$

$$z = \frac{r - \mu_r}{\sigma_r} \quad (\text{Equation 10.7})$$

Example 10.2 will be employed to illustrate the **runs test for serial randomness**. Although the sample size in Example 10.2 is less than the value recommended for the normal approximation, it will be employed to demonstrate the test. Since it provides for a more conservative test, one has the option of employing the correction for continuity (through use of Equation 10.2) to lower the likelihood of committing a Type I error.

Example 10.2 *A quality control study is conducted on a machine that pours milk into containers. The amount of milk (in liters) dispensed by the machine into 21 consecutive containers follows: 1.90, 1.99, 2.00, 1.78, 1.77, 1.76, 1.98, 1.90, 1.65, 1.76, 2.01, 1.78, 1.99, 1.76, 1.94, 1.78, 1.67, 1.87, 1.91, 1.91, 1.89. Are the successive increments and decrements in the amount of milk dispensed random?*

The sequence of up-down shifts is summarized below.

++ --- + -- ++ = + = + -- ++ **0** =

The following 20 symbols are recorded above (one less than the total number of observations): 9 pluses, indicating an increase from one measurement to the next; 10 minuses, indicating a decrease from one measurement to the next; and one zero indicating no change (for the two values of 1.91). When one or more zeroes are present in the data, the number of runs are determined if a zero is counted as a plus, as well as if a zero is counted as a minus. If the zero is counted as a plus, the total number of runs will equal 12. This is the case since prior to the zero there are 11 runs. If the zero is counted as a plus it extends the 11th run (which will now consist of three pluses instead of two pluses), and the last minus constitutes the 12th run. If the zero is counted as a minus there will still be 12 runs, since there are 11 runs up to the zero, and if the zero is viewed as a minus it joins with the last minus to comprise the 12th run, which will now consist of two minuses. In some cases if a zero is present, a different total will be obtained for the number of runs, depending upon whether the zero is viewed as a plus or minus. When the latter is true, a test statistic is obtained for each run value, and a decision is made based on both values.

If more than one zero is present in the data the analysis can get quite tedious, since one has to consider all possible combinations of counting any zero as a plus or minus. In such a case, it would probably be advisable to employ the **single-sample runs test** (see Example 10.5) or some alternative test of randomness (some of which are discussed in Section IX (the **Addendum**)). The data for Example 10.2 will now be evaluated employing Equations 10.5–10.7. For our example, $N=21$, which represents the total number of observations, and $r=12$, which represents the number of runs.

$$\mu_r = \frac{(2)(21) - 1}{3} = 13.67$$

$$\sigma_r = \sqrt{\frac{(16)(21) - 29}{90}} = 1.85$$

$$z = \frac{12 - 13.67}{1.85} = -.90$$

Since the absolute value $z = .90$ is lower than the tabled critical two-tailed value $z_{.05} = 1.96$ and the tabled critical one-tailed value $z_{.05} = 1.65$, the null hypothesis cannot be rejected, regardless of which alternative hypothesis is employed. The observed value $r = 12$ is well within chance expectation for the number of runs expected in a random distribution. The negative sign for z just indicates that the observed number of runs was less than the expected value.

The value $r = 12$ also does not achieve significance if one employs Zar's (1999) table of critical values. In the latter table, for $n = 21$, the critical two-tailed .05 values are respectively 9 and 18, and the critical one tailed .05 values are 10 and 18. In order to be significant, the obtained value of r must be equal to or less than the first number in each pair or equal to or greater than the second number in each pair. Since $r = 12$ is in between the limits that define the critical values, the null hypothesis is retained. Thus, regardless of whether we employ Equation 10.7 or Zar's (1999) table of critical values, we cannot conclude that the series for dispensing milk is not random.

It should be noted that the same set of data employed for Example 10.2 is evaluated with the **single-sample runs test** (see Example 10.5), also yielding a nonsignificant result. However, as is the case with the **single-sample runs test**, the **runs test for serial randomness** has the limitation that it can yield a nonsignificant result with data that is clearly nonrandom. Schmidt and Taylor (1970) provide an example in which the values of all the observations in the first half of a series fall below the median, while the values of all the observations in the second half of the series fall above the median value (a pattern that would not be expected in a random series). Yet in spite of the latter, the number of runs in the series falls within chance expectation if the data are analyzed with the **runs test for serial randomness**. As a general rule, runs tests are not the most stringent tests with respect to evaluating a hypothesis regarding randomness.

A discussion of the power of the **runs test for serial randomness** can be found in Levene (1952). Additional tests of randomness involving the analysis of runs can be found in Banks and Carson (1984), Phillips *et al.* (1976), and Schmidt and Taylor (1970). The latter sources describe tests that evaluate the observed versus expected frequency distribution of the length of runs for series evaluated with the **runs test for serial randomness**, as well as the **single-sample runs test**.

VII. Additional Discussion of the Single-Sample Runs Test

1. Additional discussion of the concept of randomness It is important to note that a distinction is made between a **random** and **pseudorandom** series of numbers. It is assumed that if a series is **random**, there is no algorithm that will allow one to predict at above chance which of the possible outcomes will occur on a given trial. Truly random processes are event sequences that occur within a natural context (i.e., real world phenomena such as the radioactive decay of atomic nuclei and Browning molecular motion). A **pseudorandom** series, however, is generated through use of a computer program that employs a deterministic algorithm. As a result of this, if one is privy to the rule stated by the algorithm, one will be able to correctly predict all of the numbers in the pseudorandom series in the order in which they are generated. Pseudorandom series are often employed to simulate naturally occurring random events, since their use in the latter context provides researchers with a mechanism for studying phenomena that otherwise would be impossible or problematical to evaluate. Research employing pseudorandom number series is commonly referred to as **Monte Carlo research**. Peterson (1998) notes that the use of the term Monte Carlo grew out of the work of Stanislaw Ulam and John von Neumann, two brilliant mathematicians who in the late 1940s using the earliest computers conducted seminal research on the simulation of random processes.⁶ In addition to using pseudorandom numbers for the latter, they are commonly employed today to generate outcomes in slot machines as well as in presenting random stimuli in computer software (such as in video games). More recently, the popularity of data-driven statistical methods (discussed in Section IX (the **Addendum**) of the **Mann–Whitney U test (Test 12)**) has increased the demand for reliable random number generators.

To employ pseudorandom numbers effectively within the framework of simulation, it is essential to demonstrate that any mathematically generated series is, in fact, random. Yet the latter is easier said than done. In the second volume of his classic book *Seminumerical Algorithms* (1969, 1981, 1997), Donald Knuth notes that a number of mathematicians have suggested as a definition of randomness that a series of numbers should be able to pass each of the statistical tests that have been developed for evaluating randomness. Yet Knuth (1969, 1981, 1997) notes that it is virtually impossible to identify or generate a random series that will pass each and every statistical test that has been developed. Even if one could find such a series, it is all but certain that within the series there will be one or more sequences of numbers (often quite long in duration) which by themselves will fail one or more of the statistical tests for randomness. Peterson (1998) provides an interesting discussion on the limitations of employing pseudorandom numbers to simulate naturally occurring random processes. One of the examples he cites involves what is considered to be an excellent random number generator developed by Marsaglia and Zaman (1994), which is able to pass the most demanding tests of randomness. However, the Marsaglia–Zaman random number generator (i.e., an algorithm that generates a random sequence) yielded incorrect results in a computer-simulated study of magnetism. Thus, even an excellent random number generator may be characterized by peculiarities which may compromise its usefulness in simulating certain natural processes. It should be emphasized, however, that in spite of the latter, excellent random number generators are available for effectively simulating virtually all naturally occurring random processes.

The **single-sample runs test** is only one of many tests that have been developed for assessing randomness. In point of fact, many sources do not consider runs tests to be particularly effective mechanisms for assessing randomness (e.g., Conover (1999) states that runs tests leave a lot to be desired as tests of randomness, since they are very low in statistical power.). Section IX (the **Addendum**) describes alternative tests for randomness, as well as presenting some algorithms for generating pseudorandom numbers.

VIII. Additional Examples Illustrating the Single-Sample Runs Test

As is the case with Example 10.1, Examples 10.3–10.6 all involve series in which $N = 20$, $n_1 = n_2 = 10$, and $r = 11$. By virtue of employing identical data, the latter examples all yield the same result as Example 10.1. Example 10.6 illustrates the application of the **single-sample runs test** to a design involving two independent samples.⁷ In Examples 10.1 and 10.3–10.5 it is implied that if the series involved are, in fact, random, it is probably reasonable to assume in the underlying population $\pi_1 = \pi_2 = .5$ (in other words, that each alternative has an equal likelihood of occurring in the underlying population, even if the latter is not reflected in the sample data). Example 10.7 illustrates the application of the **single-sample runs test** to a design in which it is known that in the underlying population $\pi_1 \neq \pi_2 \neq .5$.

Example 10.3 *A meteorologist conducts a study to determine whether humidity levels recorded at 12 noon for 20 consecutive days in July 1995 are distributed randomly with respect to whether they are above or below the average humidity recorded during the month of July during the years 1990 through 1994. Recorded below is a listing of whether the humidity for 20 consecutive days is above (+) or below (–) the July average.*

+ + + – – – + + – – + – + – – – + +

Do the data indicate that the series of temperature readings is random?

Example 10.4 *The gender of 20 consecutive patients who register at the emergency room of a local hospital is recorded below (where: M = Male; F = Female).*

F F F M M M F F M M F M F M F M M M F F

Do the data suggest that the gender distribution of entering patients is random?

Example 10.5 *A quality control study is conducted on a machine that pours milk into containers. The amount of milk (in liters) dispensed by the machine into 21 consecutive containers follows: 1.90, 1.99, 2.00, 1.78, 1.77, 1.76, 1.98, 1.90, 1.65, 1.76, 2.01, 1.78, 1.99, 1.76, 1.94, 1.78, 1.67, 1.87, 1.91, 1.91, 1.89. If the median number of liters the machine is programmed to dispense is 1.89, is the distribution random with respect to the amount of milk poured above versus below the median value?*

In Example 10.5 it can be assumed that if the process is random the scores should be distributed evenly throughout the series, and that there should be no obvious pattern with respect to scores above versus below the median. Thus, initially we list the 21 scores in sequential order with respect to whether they are above (+) or below (–) the median. Since one of the scores (that of the last container) is at the median, it is eliminated from the analysis. The latter protocol is employed for all scores equal to the median when the **single-sample runs test** is used within this context. The relationship of the first 20 scores to the median is recorded below.

+ + + – – – + + – – + – + – – – + +

Since the above sequence of runs is identical to the sequence observed for Examples 10.1, 10.3, and 10.4, it yields the same result. Thus, there is no evidence to indicate that the

distribution is not random. Presence of a nonrandom pattern due to a defect in the machine can be reflected in a small number of large cycles (i.e., each cycle consists of many trials). Thus, one might observe 10 consecutive containers that are overfilled followed by 10 consecutive containers that are underfilled. A nonrandom pattern can also be revealed by an excess of runs attributed to multiple small cycles (i.e., each cycle consists of few trials).

The reader should take note of the fact that although the **Wilcoxon signed-ranks test (Test 4)** can also be employed to evaluate the data for Example 10.5, it is not appropriate to employ the latter test for evaluating a hypothesis regarding randomness. The **Wilcoxon signed-ranks test** can be used to evaluate whether or not the data indicate that the true median value for the machine is some value other than 1.89. It does not provide information concerning the ordering of the data. It should also be noted that the data for Example 10.5 are identical to that employed for Example 10.2. Note that in the latter example the **runs test for serial randomness** was employed to evaluate the hypothesis of randomness (in reference to increments and decrements of liters on successive trials), and also concluded that the evidence did not suggest a lack of randomness.

Example 10.6 *In a study on the efficacy of an antidepressant drug, each of 20 clinically depressed patients is randomly assigned to one of two treatment groups. For 6 months one group is given the antidepressant drug and the other group is given a placebo. After 6 months have elapsed, subjects in both groups are rated for depression by a panel of psychiatrists who are blind with respect to group membership. Each subject is rated on a 100 point scale (the higher the rating, the greater the level of depression). The depression ratings for the two groups follow.*

Drug group:	20, 25, 30, 48, 50, 60, 70, 80, 95, 98
Placebo group:	35, 40, 42, 52, 55, 62, 72, 85, 87, 90

Do the data indicate there is a difference between the groups?

Since it is less powerful than alternative procedures for evaluating the same design (which typically contrast groups with respect to a measure of central tendency), the **single-sample runs test** is not commonly employed in evaluating a design involving two independent samples. Example 10.6 will, nevertheless, be used to illustrate its application to such a situation. In order to implement the runs test, the scores of the 20 subjects are arranged ordinally with respect to group membership as shown below (Where **D** represents the Drug group and **P** represents the Placebo group).

20	25	30	35	40	42	48	50	52	55	60	62	70	72	80	85	87	90	95	98
D	D	D	P	P	P	D	D	P	P	D	P	D	P	D	P	P	P	D	D

Runs are evaluated as in previous examples. In this instance, the two categories employed in the series represent the two groups from which the scores are obtained. When the scores are arranged ordinally, if there is a difference between the groups it is expected that most of the scores in one group will fall to the left of the series, and that most of the scores in the other group will fall to the right of the series. More specifically, if the drug is effective one will predict that the majority of the scores in the Drug group will fall to the left of the series. Such an outcome will result in a small number of runs. Thus, if the number of runs is equal to or less than the tabled critical lower limit at the prespecified level of significance, one can conclude that the pattern of the data is nonrandom. Such an outcome will allow the researcher to conclude that there is a significant difference between the groups. Since $n_1 = n_2 = 10$ and $r = 11$, the data for Example 10.6 are identical to that obtained for Examples 10.1, 10.3, and 10.4. Analysis of the

data do not indicate that the series is nonrandom, and thus one cannot conclude that the groups differ from one another (i.e., represent two different populations).

Let us now consider two other possible patterns for Example 10.6. The first pattern depicted below contains $r = 2$ runs. It yields a significant result since in Table A8, for $n_1 = n_2 = 10$, any number of runs equal to or less than 6 is significant at the .05 level. Thus, the pattern depicted below will lead the researcher to conclude that the groups represent two different populations.

D D D D D D D D D D P P P P P P P P P P

Consider next the following pattern:

D D D D D P P P P P P P P P P D D D D D

Since the above pattern contains $r = 3$ runs, it is also significant at the .05 level. Yet inspection of the pattern suggests that a test which compares the mean or median values of the two groups will probably not result in a significant difference. This is based on the observation that the group receiving the drug contains the five highest and five lowest scores. Thus, if the performance of the Drug group is summarized with a measure of central tendency, such a value will probably be close to the analogous value obtained for the placebo group (whose scores cluster in the middle of the series). Nevertheless, the pattern of the data certainly suggests that a difference with respect to the variability of scores exists between the groups. In other words, half of the people receiving the drug respond to it favorably, while the other half respond to it poorly. Most of the people in the placebo group, on the other hand, obtain scores in the middle of the distribution. The above example illustrates the fact that in certain situations the **single-sample runs test** may provide more useful information regarding two independent samples than other tests which are more commonly used for such a design — specifically, the ***t* test for two independent samples (Test 11)** and the **Mann–Whitney *U* test (Test 12)**, both of which evaluate measures of central tendency. The pattern of data depicted for the series under discussion is more likely to be identified by a test that contrasts the variability of two independent samples. In addition to the **single-sample runs test**, other procedures (discussed later in the book) that are better suited to identify differences with respect to group variability are the **Siegel–Tukey test of equal variability (Test 14)** and the **Moses test for equal variability (Test 15)**.

Example 10.7 *A quality control engineer is asked by the manager of a factory to evaluate a machine that packages glassware. The manager informs the engineer that 90% of the glassware processed by the machine remains intact, while the remaining 10% of the glassware is cracked during the packaging process. It is suspected that some cyclical environmental condition may be causing the machine to produce breakages at certain points in time. In order to assess the situation, the quality control engineer records a series comprised of 1000 pieces of glassware packaged by the machine over a two-week period. It is determined that within the series 890 pieces of glassware remain intact and that 110 are cracked. It is also determined that within the series there are only 4 runs. Do the data indicate the series is nonrandom?*

In Example 10.7, $N = 1000$, $n_1 = 890$, $n_2 = 110$, and $r = 4$. Employing these values in Equation 10.1, the value $z = -3.12$ is computed. In employing the latter equation, the computed value for the expected number of runs is $\mu_r = 196.8$, which is well in excess of the observed value $r = 4$.

$$z = \frac{4 - \left[\frac{(2)(890)(110)}{890 + 110} + 1 \right]}{\sqrt{\frac{(2)(890)(110)[(2)(890)(110) - 890 - 110]}{(890 + 110)^2(890 + 110 - 1)}}} = -3.12$$

Employing **Table A8**, we determine that the absolute value $z = 3.12$ is greater than the tabled critical two-tailed values $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed values $z_{.05} = 1.65$ and $z_{.01} = 2.33$. Thus, the nondirectional alternative hypothesis is supported at both .05 and .01 levels. Since the obtained value of z is negative, the directional alternative hypothesis predicting too few runs is supported at the both the .05 and .01 levels. Obviously, the directional alternative hypothesis predicting too many runs is not supported.

Note that in Example 10.7 the plant manager informs the quality control engineer that the likelihood of a piece of glassware cracking is $\pi_1 = .9$, whereas the likelihood of it being intact is $\pi_2 = .1$. Thus, each of the two alternatives (**Intact** versus **Cracked**) are not equally likely to occur on a given trial. The observed proportion of cases in each of the two categories $p_1 = 890/1000 = .89$ and $p_2 = 110/1000 = .11$ are quite close to the values $\pi_1 = .9$ and $\pi_2 = .1$. As noted earlier in the discussion of the **single-sample runs test**, if the observed proportions are substantially different from the values assumed for the population proportions, the test will not identify such a difference, and the analysis of runs will be based on the observed values of the proportions in the series, regardless of whether or not they are consistent with the underlying population proportions. The question of whether the proportions computed for the sample data are consistent with the population proportions is certainly relevant to the issue of whether or not the series is random. However, the **binomial sign test for a single sample (Test 9)** and the **chi-square goodness-of-fit test (Test 8)** are the appropriate tests to employ to evaluate the latter question.

IX. Addendum

1. The generation of pseudorandom numbers In Section VII the distinction between random and pseudorandom numbers was discussed. In this section a number of pseudorandom number generators will be described. Various sources (e.g., Banks and Carson (1984), Phillips *et al.* (1976), and Schmidt and Taylor (1970)) note that an effective random number generator is characterized by the following properties: a) The numbers generated should conform as closely as possible to a **uniform distribution**. By the latter it means that each of the possible values in the distribution must have an equal likelihood of occurring. Thus, if each of the random numbers is an integer value between 0 and 9, each of the ten digits 0, 1, 2, 3, 4, 5, 6, 7, 8, 9 must have an equal likelihood of occurring; b) The random number generator should have a **long period**. The period is the number of random numbers that are generated before the sequence begins to repeat. The term **cycling** is used when a sequence of numbers begins to repeat itself; c) A good generator should not **degenerate**. Degeneracy is when a random number generator at some point continually produces the same number; d) Since a researcher may wish to repeat the same experiment with the same set of numbers, a good random number generator should allow one to reproduce the same sequence of numbers, as well as having the ability to produce a unique sequence of numbers each time it is run; and e) The structure of a random number generator should be such that it can be executed quickly by a computer, and not utilize an excessive amount of computer memory. Most random number generators begin with initial values called a **seed**, **constants**, and/or a **modulus**. Certain characteristics of these values (such as their magnitude or whether they are a prime number⁸) may be critical in determining the quality of the random series that will

be produced by a generator. At this point a number of different types of random number generators will be described. Keep in mind that since quality random number generators involve the use of very large numbers and employ an excessive number of iterations (an iteration is the repetitive use of the same equation or set of mathematical operations), they require the use of a computer.

The midsquare method The first method for generating pseudorandom numbers was the **midsquare method** developed by John von Neumann in 1946 for simulation purposes. The midsquare method begins with a **seed** number, which is an initial value that the user arbitrarily selects. The first step of the midsquare method requires that the seed is squared, and the first random number will be the middle r digits of the resulting number. Each subsequent number is obtained by squaring the previous number, and once again employing the middle r digits of the resulting number as the next random number. The process is continued until the sequence of numbers cycles or degenerates.

To illustrate the midsquare method, assume that the seed number is 4931. The square of 4931 is 24314761. The middle four digits 3147 will represent the first random number. When we square 3147, we obtain 9903609. The middle four digits of the latter number 0360 will represent the next random number. When we square 0360, we obtain 129600. The middle four digits of the latter number 2960 will represent the next random number. As noted above, the process is continued until the sequence of numbers cycles or degenerates. Since the midsquare method tends to degenerate rapidly (resulting in a short period), it is seldom used today.

The midproduct method Although the **midproduct method** is superior to the midsquare method, it has a relatively short period compared to the best of the random number generators that are employed today. In the midproduct method one starts with two seed numbers (to be designated m_1 and m_2), each number containing the same number of digits. The values m_1 and m_2 are multiplied, and the middle r digits of the resulting value, designated m_3 , are used to represent the first random number. m_3 is now multiplied by m_2 , and the middle r digits of the resulting number are designated as the second random number. The process is continued until the sequence of numbers cycles or degenerates.

To illustrate the midproduct method, assume we begin with the two seed numbers 4931 and 7737, which when multiplied yield 38151147. The middle four digits of the latter number are 1511, which will represent the first random number. We next multiply the second seed (7737) by 1511, which yield 11690607. The middle four digits of the latter number are 6906, which will represent the next random number. We next multiply 1511 by 6906 yielding 10434966. The middle four digits of the latter number are 4349, which represent the next random number. As noted above, the process is continued until the sequence of numbers cycles or degenerates.

A variant of the midproduct method employs just one seed and another value called a **constant multiplier**. The seed is multiplied by the constant multiplier, and the first random number is the middle r digits of the resulting product. That value is then multiplied by the constant multiplier, and the second random number is the middle r digits of the resulting product, and so on. The process is continued until the sequence of numbers cycles or degenerates.

To illustrate this variant of the midproduct method, assume we begin with the seed 4931 and the constant multiplier 7737. When we multiply these two values we obtain 38151147. The middle four digits of the latter number are 1511, which will represent the first random number. We next multiply 1511 by the constant multiplier 7737 obtaining 11690607. The middle four digits of the latter number are 6906, which will represent the next random number. The value 6906 is multiplied by the constant multiplier 7737 yielding 53431722. The middle four digits of

the latter number are 4317, which will represent the next random number. As noted above, the process is continued until the sequence of numbers cycles or degenerates.

The Linear congruential method **Congruential methods** are the most commonly used mechanisms employed today for generating random numbers. Congruential random number generators employ **modular arithmetic**, which means that they employ as a random number the remainder that results after dividing one number by another. To describe the use of modular arithmetic within the context of the congruential method, we will let the notation *mod* represent **modulus**. The notation $y \bmod m$ means that some number designated by the symbol y is divided by the modulus which is represented by the value m . Whatever remainder results from this division will be employed as a random number.

The **linear congruential method**, which was developed by the mathematician Derrick Lehmer, is probably the most commonly used of the random number generators that are based on the congruential method. The linear congruential method produces random numbers that fall in the range 0 to $m - 1$. It is based on the following recursive relationship (a recursive relationship is one in which each result is computed by employing the information from the previous result): $x_{i+1} = (ax_i + c) \bmod m$. In the aforementioned equation, a is a **constant multiplier**, c is referred to as the **additive constant** or **increment**, and m is the **modulus**. All of the aforementioned values remain unchanged each time the equation is employed. The initial value of x_i (which we will refer to as x_0) will be the **seed**. When the equation is employed the first time, the seed (x_0) is multiplied by the constant multiplier (a) and the additive constant (c) is added to the product. The latter value is divided by the modulus (m), and the remainder after the division represents the value on the left side of the equation (x_{i+1}). This latter value will represent the first random number (x_1). The equation is then employed again, using the value x_1 in the right side of the equation to represent x_i . The resulting value will represent the second random number. This process is continued until the sequence of numbers cycles or degenerates.

To illustrate the linear congruential method, assume we begin with the following values: **Seed** = $x_0 = 47$; **Constant multiplier** = $a = 17$; **Additive constant** = $c = 79$; **Modulus** = 100. Our initial equation is thus, $x_1 = [(17)(47) + 79] \bmod 100$. The computed value of $x_1 = 78$, since $(17)(47) + 79 = 878$, which when divided by 100 yields 8 with a remainder of 78. Thus 78 will represent the first random number. The equation is employed again using the value $x_1 = 78$ to represent x_i on the right side of the equation. Thus, $x_2 = [(17)(78) + 79] \bmod 100$ which yields 1405 divided by the modulus of 100. When 1405 is divided by 100, we obtain 14 with a remainder of 5. Thus, 5 is our second random number. The equation is then employed again using the value $x_2 = 5$ to represent x_i on the right side of the equation. Thus, $x_3 = [(17)(5) + 79] \bmod 100$ which yields 164 divided by the modulus of 100. When 164 is divided by 100, we obtain 1 with a remainder of 64. Thus, 64 is our third random number. As noted above, this process is continued until the sequence of numbers cycles or degenerates. It should be noted that in order to generate a sequence of random numbers that are of high quality with a congruential generator, the value of the modulus must be quite large. Bennett (1998) notes that Lehmer suggested the value 2,147,483,647 (which is equivalent to $(2^{31} - 1)$) for the modulus of congruential generators, and the latter value is, in fact, employed in many linear congruential generators. The values of the constant multiplier and additive constant vary from generator to generator. Bang *et al.* (1998) note that when the additive constant $c = 0$, the term **multiplicative congruential generator** is employed in reference to a linear congruential generator. In point of fact, most of the commonly used congruential random number generators are multiplicative congruential (i.e., since $c = 0$, the congruential equation becomes $x_{i+1} = ax_i \bmod m$).

Note that in all of the random number generators that have been described in this section, an integer number has been employed to represent each random number. In the case of the midsquare and midproduct methods, each value generated was a four-digit number that fell in the

range 0000 to 9999. If we had wanted to, we could have selected the middle two or three digits or just one digit (instead of the middle four digits) from the product that was derived from multiplication. Also, by increasing the size of the seed(s) and/or the constant multiplier, a larger product can be obtained allowing one to select the middle six, seven eight, etc. digits as a random number. Often when random generators are employed, the range of random numbers one desires may be very limited. Let us assume that we generate four-digit numbers as illustrated above, but want our sequence of random numbers to be comprised of two-digit numbers. The latter can be easily achieved by breaking each four-digit number into two numbers comprised of two digits, each number falling in the range 00 to 99. If one-digit numbers are desired, four one-digit numbers can be extracted from the four-digit number. If one is interested in a binary series of numbers, in which the only values employed are 0 and 1, each odd digit can be employed to represent one alternative and each even digit the other alternative. If one only wants three values, the digits 0, 1, 2 can be employed to represent one value, 3, 4, 5, a second value, and 6, 7, 8 a third value (the digit 9 would just be ignored when it occurs). By using the aforementioned logic, the number(s) generated can be formatted to represent however many alternatives one wants to employ within a sequence of random numbers.

In actuality, most random number generators return a value that falls within the range 0 to 1. If one wished to convert any of the random numbers derived in this section into a value that falls within that range, each value can be divided by 10 raised to the appropriate power. In other words, if we take the random number 1511 generated earlier and divide it by 10000, we obtain .1511. If we break 1511 into the two numbers 15 and 11, the latter values can be converted into .15 and .11 by dividing them by 100. Congruential generators typically return decimal values to represent random numbers. Thus, instead of expressing the remainder as an integer (as was done above), a decimal format is employed. For example, consider the value 78 used to represent the first random number generated by a linear congruential generator. The latter value was the remainder when 878 was divided by 100. The usual way of expressing the result of the division $878/100$ is 8.78. The decimal part of the result, .78, can be employed to represent a random number in the range 0 to 1.

If one happens to be employing a random number generator that yields values between 0 and 1, it is easy to convert the latter values into integer numbers that fall within a specified range of values. As an example, let us assume a computer generates a series of random numbers that are in the range between 0 and 1, and that we wish to convert each number into an integer value between 1 and 6 in order to simulate the throwing of a die. If we multiply each of the numbers that fall in the range 0 to 1 by 6 (i.e., the value that represents the largest integer value) and employ the integer part of the result (i.e., the number to the left of the decimal) with one unit added, we will create a random series of integer numbers that fall in the range 1 to 6. (The only exception to this will be if the random number generated equals 1, which when multiplied by 6 with 1 added will yield the value 7.) To illustrate, if the first random number generated by the computer is .9888 and we multiply the latter number by 6 we obtain 5.9328. Since the value 5 represents the integer number to the left of the decimal, we add one unit to it making it the number 6. The latter value will represent the first outcome for the die. If the next random number the computer generates is .0321, the latter value multiplied by 6 equals .1926. Since the value to the left of the decimal is a zero, we add 1 to it, and the resulting value of 1 will represent the next outcome for the die.

Bang *et al.* (1998) note that at the current time there are three types of random number generators that are commonly employed. The first kind are congruential random number generators which were discussed earlier. The other two types of random number generators that are frequently used are: a) The **shift-register generator** (also known as the **Tausworthe generator**), which employs the binary structure of computers; and b) The **Fibonacci generator** (also

known as the **additive generator**). Representative of the latter type of generator is the Marsaglia–Zaman method, which employs the **Fibonacci sequence**. The latter is a sequence of numbers in which, except for the first value, every number is the sum of the previous two numbers. Thus: 1, 1, 2, 3, 5, 8, 13, 21, etc. Peterson (1998) describes how the Fibonacci sequence was utilized by Marsaglia and Zaman to generate a random numbers series with an exceptionally long period. Bang *et al.* (1998), Banks and Carson (1984), Bennett (1998), Gruenberger and Jaffray (1965), James (1990), Knuth (1969, 1981, 1997), Peterson (1998), Phillips *et al.* (1976), and Schmidt and Taylor (1970) are sources which can provide the reader with a more detailed description and/or critique of random number generators.

2. Alternative tests of randomness⁹ The **single-sample runs test** is one of many tests that have been developed for assessing randomness. Most of the alternative procedures for assessing randomness allow one to evaluate series in which, on each trial, there are two or more possible outcomes. A general problem with tests of randomness is that they do not employ the same criteria for assessing randomness. As a result of this some tests are more stringent than others, and thus it is not uncommon that a series of numbers may meet the requirements of one or more of the available tests of randomness, yet not meet the requirements of one or more of the other tests. This section will discuss some of the more commonly employed tests for evaluating random number sequences.

Test 10b: The frequency test The **frequency test** (also known as the **equidistribution test**), which is probably the least demanding of the tests of randomness, assesses randomness on the basis of whether *k* or more equally probable alternatives occur an equal number of times within a series. The data for the **frequency test** are evaluated with the **chi-square goodness-of-fit test**, and when *k* = 2 the **binomial sign test for a single sample** (as well as the large sample normal approximation) can be employed. The **Kolmogorov–Smirnov goodness-of-fit test for a single sample (Test 7)** can also be employed to assess the uniformity of the scores in a distribution. The interested reader should consult Banks and Carson (1984) and Schmidt and Taylor (1970) for a description of how the latter test is employed within this context.

Since the **frequency test** only assesses a series with respect to the frequency of occurrence of each of the outcomes, it is insensitive to systematic patterns that may exist within a series. To illustrate this limitation of the **frequency test**, consider the following two binary series consisting of Heads (**H**) and Tails (**T**), where $\pi_1 = \pi_2 = .5$.

Series A: H H H T H T T T H T H H T H T T T H T H
Series B: H T H T H T H T H T H T H T H T H T

Inspection of the data indicates that both **Series A** and **B** are comprised of 10 **Heads** and 10 **Tails**. Since the number of times each of the alternatives occurs is at the chance level (i.e., each occurs in 50% of the trials), if one elects to analyze either series employing either the **chi-square goodness-of-fit test** or the **binomial sign test for a single sample**, both series will meet the criterion for being random. However, visual inspection of the two series clearly suggests that, as opposed to **Series A**, **Series B** is characterized by a systematic pattern involving the alternation of **Heads** and **Tails**. This latter observation clearly suggests that **Series B** is not random.

At this point, the **frequency test** and the **single-sample runs test** will be applied to the same set of data. Specifically, both tests will be employed to evaluate whether or not the series below (which consists of *N* = 30 trials) is random. In the series, each of the runs has been underlined.

H H H H H T H T H H H T H T H T H H H T T T T H H H H H H H H

Since $k = 2$, the **binomial sign test for a single sample** will be employed to represent the **frequency test**. When the **binomial sign test** is employed, the null hypothesis that is evaluated is: $H_0: \pi_1 = .5$ (since it is assumed that $\pi_1 = \pi_2 = .5$). For both the **binomial sign test for a single sample** and the **single-sample runs test**, it will be assumed that a nondirectional alternative hypothesis is evaluated.

In the series that is being evaluated, the number of **Heads** is $n_1 = 21$ and the number of **Tails** is $n_2 = 9$. Employing Equation 9.9 (which is the continuity-corrected normal approximation for the **binomial sign test for a single sample**), the value $z = 2.01$ is computed.

$$z = \frac{|21 - (30)(.5)| - .5}{\sqrt{(30)(.5)(.5)}} = 2.01$$

Since the obtained value $z = 2.01$ is greater than the tabled critical two-tailed value $z_{.05} = 1.96$, the nondirectional alternative hypothesis $H_1: \pi_1 \neq .5$ is supported. Thus, based on the above analysis with the **binomial sign test for a single sample**, one can conclude that the series is not random.

In evaluating the same series with the **single-sample runs test**, we determine that there are $r = 13$ runs in the data. The expected number of runs is $[(2)(21)(9)]/(21 + 9) + 1 = 13.6$, which is barely above the observed value $r = 13$. Employing Equation 10.1, the value $z = -.27$ is computed.¹⁰

$$z = \frac{13 - \left[\frac{(2)(21)(9)}{21 + 9} + 1 \right]}{\sqrt{\frac{(2)(21)(9)[(2)(21)(9) - 21 - 9]}{(21 + 9)^2(21 + 9 - 1)}}} = -.27$$

Since the obtained absolute value $z = .27$ is less than the tabled critical two-tailed value $z_{.05} = 1.96$, the nondirectional alternative hypothesis for the runs test is not supported. Thus, based on the above analysis with the **single-sample runs test**, one can conclude that the series is random.

The fact that a significant result is obtained when the **binomial sign test for a single sample** is employed to evaluate the series, reflects the fact that the latter test only takes into account the number of observations in each of the two categories, but does not take into consideration the ordering of the data. The **single-sample runs test**, on the other hand, is sensitive to the ordering of the data, yet will not always identify a nonrandom series if nonrandomness is a function of the number of outcomes for each of the alternatives.

There will also be instances where one may conclude a series is random based on an analysis of the data with the **single-sample runs test**, yet not conclude the series is random if the **binomial sign test for a single sample** is employed for the analysis. Such a series, consisting of 15 **Heads** and 15 **Tails**, is depicted below.

HHHHHHHHHHHHHHH TTTTTTTTTTTTTTTT

When Equation 9.7 (the normal approximation of the **binomial sign test for a single sample**) is employed, it yields the following result: $z = [15 - (30)(.5)]/\sqrt{(30)(.5)(.5)} = 0$. Equation 9.9, the continuity-corrected equation, yields the absolute value $z = .18$. Since the latter values are less than the tabled critical two-tailed value $z_{.05} = 1.96$, the result is not significant, and thus one can conclude that the series is random. When, however, the same series, which

consists of only two runs, is evaluated with Equation 10.1 (the equation for the normal approximation of the **single-sample runs test**), it yields the following result: $z = (r - \mu_r)/\sigma_r = (2 - 16)/2.69 = -5.20$. Since the absolute value $z = 5.20$ is greater than the tabled critical two-tailed values $z_{.05} = 1.96$ and $z_{.01} = 2.58$, the result is significant at both the .05 and .01 levels. Thus, if one employs the **single-sample runs test**, one can conclude that the series is not random.

One final set of data will be evaluated with the **frequency test**. The data to be presented (which were generated by a computer program) will also be evaluated with three other tests of randomness which will be presented in this section — specifically, the **gap test**, the **poker test**, and the **maximum test**. Keep in mind that in computer simulation research, the number of digits that comprise a series of random numbers will typically be more than 120 digits used in the data set to be presented. When random number generators are evaluated, millions or even billions of digits are generated and analyzed. One should keep in mind that within a random series of millions of numbers, there will undoubtedly be sequences of shorter duration that in and of themselves would not pass a test for randomness. In any event, the series presented below consists of 120 digits in the range 0–9.

8, 9, 3, 7, 2, 3, 0, 2, 3, 1, 4, 7, 8, 5, 6, 2, 0, 9, 6, 8, 7, 5, 3, 0, 7, 8, 9, 6, 3, 5,
 9, 9, 8, 4, 6, 3, 7, 9, 1, 0, 8, 3, 7, 6, 1, 0, 0, 3, 8, 9, 5, 6, 6, 7, 4, 1, 2, 0, 3, 6,
 7, 8, 8, 8, 9, 9, 4, 5, 3, 3, 1, 1, 1, 6, 0, 0, 8, 7, 7, 3, 9, 7, 5, 2, 0, 3, 8, 6, 0, 4,
 6, 3, 0, 2, 8, 6, 7, 0, 0, 1, 2, 5, 0, 5, 7, 9, 0, 8, 6, 4, 3, 2, 5, 8, 9, 6, 1, 0, 7, 8

The data are evaluated with the **chi-square goodness-of-fit test**. There are 10 categories, one corresponding to each of the 10 digits. Each digit followed by its observed frequency in the 120 digit series is presented: **0** (17); **1** (9); **2** (8); **3** (15); **4** (6); **5** (9); **6** (14); **7** (14); **8** (16); **9** (12). If (as it is employed in Equation 8.1) n represents the total number of observations, the expected frequency for each digit is $E_i = n\pi_i = (120)(.1) = 12$. Since the chi-square analysis will be based on $k = 10$ categories/cells, the degrees of freedom will be $df = k - 1 = 10 - 1 = 9$. When the data are evaluated with Equation 8.2, the value $\chi^2 = 10.65$ is computed. [Table 10.1](#) provides a summary of the analysis.

Table 10.1 Summary of Chi-Square Analysis for Frequency Test

Cell/Digit	Observed Frequency (O)	Expected Frequency (E)	$\frac{(O - E)^2}{E}$
0	17	12	2.08
1	9	12	.75
2	8	12	1.33
3	15	12	.75
4	6	12	3.00
5	9	12	.75
6	14	12	.33
7	14	12	.33
8	16	12	1.33
9	12	12	.00
Sums	120	120	$\chi^2 = 10.65$

Employing [Table A4](#) (**Table of the Chi-Square Distribution**) in the **Appendix**, for $df=9$, the tabled critical values are $\chi^2_{.05} = 16.92$ and $\chi^2_{.01} = 21.67$. Since the obtained value $\chi^2 = 10.65$ is less than $\chi^2_{.05} = 16.92$, the null hypothesis is retained. Thus, the data are consistent with the series being random.

Test 10c: The gap test Described in Banks and Carson (1984), Gruenberger and Jaffray (1965), Knuth (1969, 1981, 1997), Phillips *et al.* (1976), and Schmidt and Taylor (1970), the **gap test** evaluates the number of **gaps** between the appearance of a digit in a series and the reappearance of the same digit. Thus, if we have $k = 10$ digits and each of the digits is equally likely to occur, it would be expected that if the distribution of digits in a series consisting of n digits is random, the average gap/interval for the reoccurrence of each digit will equal $k = 10$. A gap for any digit can be determined by selecting that digit and counting until the next appearance of the same digit. To illustrate the concept of a gap, consider the following series of digits: 0121046720. For the digit 0 we can count two gaps of lengths 3 and 4 respectively. This is the case, since the number of digits between the first 0 and the second 0 is 3, and the number of digits between the second 0 and the third 0 is 4. In conducting the **gap test**, all of the gaps for each of the digits in the series are counted, after which the computed gap values are evaluated. The analysis of the data for a series within the framework of the **gap test** can employ one or more statistical tests that have been discussed in this book: a) The **single-sample z test (Test 1)** can be employed to contrast the computed mean gap value versus the expected mean gap value for each digit; b) The **single-sample chi-square test for a population variance (Test 3)** can be employed to contrast the observed versus expected variance of the gaps values for each digit; and c) The **chi-square goodness-of-fit test** can be employed to compare the observed versus expected gap lengths of a specific value for each or all of the digits separately or together.

To illustrate some of the analyses that can be conducted on gap values, we will employ the same 120 digit series evaluated earlier with the **frequency test**. The number of gaps for any digit in a series will be one less than the frequency of occurrence of that digit in the series. Consequently the total number of gaps in the series will be $n - k$ (i.e., the total number of digits generated less the number of digit categories employed). Thus, in the case of a 120 digit series employing 10 digit values, the total number of gaps in the series will equal $120 - 10 = 110$. It was noted in the **frequency test** analysis of the 120-digit series, that the digit 0 appears 17 times. Thus, there are 16 gaps for the value 0. Inspection of the series will reveal that the first gap length is 9, the second 6, and so on. The 16 gap lengths for the digit 0 are as follows: 4 gaps of length 3, 3 gaps of length 0, 2 gaps of length 10, and 1 gap of lengths 4, 5, 6, 8, 9, 15, and 16. The computed mean (through use of Equation I.1) and estimated population variance (through use of Equation I.5) of the 16 gap lengths are $\bar{X} = 5.94$ and $\hat{s}^2 = 25.00$. The expected value for the mean (μ) is equal to k , the number of digit categories. Thus, $\mu = k = 10$. The expected value for the variance of the gaps for a digit is $\sigma^2 = k(k - 1)$. Thus, for each of the ten digits the expected variance is $\sigma^2 = 10(10 - 1) = 90$.

With respect to the data for the digit 0, the **single-sample z test** (employing Equation 1.3) will be used to evaluate the null hypothesis that for the digit 0, gap values in the sample are consistent with a population that has a mean value of 10. The **single-sample chi-square test for a population variance** (employing Equation 3.2) will be used to evaluate the null hypothesis that for the digit, 0 gap values in the sample are consistent with a population that has a variance of 90. In a random distribution both of the aforementioned null hypotheses would not be rejected, not only in the case of the digit 0, but also in the case of any of the other nine digits.

When the **single-sample z test** is employed to evaluate the hypothesis about the mean value of the gaps for the digit 0, it yields the value $z = -1.69$. Note that the value 9.49 employed in Equation 1.3 represents the square root of the expected population variance (i.e., $\sqrt{\sigma^2} = \sqrt{90} = 9.49$). The value $n = 16$ employed in computing $\sigma_{\bar{X}}$ with Equation 1.2, represents the number of gaps.

$$z = \frac{\bar{X} - \mu}{\sigma_{\bar{X}}} = \frac{5.94 - 10}{\frac{9.49}{\sqrt{16}}} = -1.69$$

Since the absolute value $z = 1.69$ is greater than the tabled critical one-tailed value $z_{.05} = 1.65$, the directional alternative hypothesis predicting that the sample came from a population with a mean gap value less than 10 (since the value of z is negative) is supported at the .05 level, but not at the .01 level (since $z = 1.69$ is less than the tabled critical one-tailed value $z_{.01} = 2.33$). Since the absolute value $z = 1.69$ is less than the tabled critical two-tailed value $z_{.05} = 1.96$, the nondirectional alternative hypothesis predicting that the sample came from a population with mean gap value other than 10 is not supported. However, the fact that the one-tailed analysis yields a significant result suggests that the average gap value of $\bar{X} = 5.94$ for the digit 0 is inconsistent with what one would expect in a random distribution of digits.

When the **single-sample chi-square test for a population variance** is employed to evaluate the hypothesis about the variance of the gaps for the digit 0, it yields the value $\chi^2 = 4.17$.

$$\chi^2 = \frac{(n - 1) \hat{s}^2}{\sigma^2} = \frac{(16 - 1)(25.00)}{90} = 4.17$$

Employing **Table A4**, for $df = n - 1 = 15$, the tabled critical one-tailed values in the lower tail of the chi-square distribution are $\chi_{.05}^2 = 7.26$ and $\chi_{.01}^2 = 5.23$, and the tabled critical two tailed values are $\chi_{.05}^2 = 6.26$ and $\chi_{.01}^2 = 4.60$ (the lower tail is employed since the value computed for the estimated population variance is less than the hypothesized population variance). Since the obtained value $\chi^2 = 4.17$ is less than all of the aforementioned critical values, the null hypothesis is rejected, regardless of which alternative hypothesis is employed. The data seem to clearly suggest that the sample came from a population with a variance gap value less than 90. Thus, the result of the evaluation of the mean and variance of the digit 0 is inconsistent with what would be expected in a random distribution of digits.

The above described analyses can also be employed to evaluate the means and estimated variances of the other nine digits. However, as noted in Section VI of the **chi-square goodness-of-fit test**, when a large number of tests are conducted on a set of data, the likelihood of committing at least one Type I error increases dramatically. The general issue of conducting multiple tests is discussed in detail in Section VI of the **single-factor between-subjects analysis of variance (Test 21)**. Nevertheless, it is likely that tests for multiple digits will yield significant results in the case of analyzing the means and/or variances of gap values for specific digits in a distribution that is not random.

A common test for randomness that evaluates gaps contrasts the observed frequencies of different gap values with their expected frequencies. In a distribution in which there are $k = 10$ digit categories, the probability that a gap of length r will occur (for any digit) is $P(r) = (.1)(.9)^r$. Thus, the likelihood of finding for any of the ten digits a gap of length 0 will be $(.1)(.9)^0 = .1$. The likelihood of finding a gap of length 1 will be $(.1)(.9)^1 = .09$. The likelihood of finding a gap of length 2 will be $(.1)(.9)^2 = .081$, and so on. The **chi-square goodness-of-fit test**, which will be demonstrated below, can be employed to compare the values of the observed and expected gap lengths for the whole series. If a significant difference is obtained, it would warrant the conclusion that the series is not random. The **Kolmogorov–Smirnov goodness-of-fit test for a single sample** can also be employed to assess the distribution of gap lengths within a series. The interested reader should consult Banks and Carson (1984) and Schmidt and Taylor (1970) for a description of how the latter test is employed within this context.

Table 10.2 summarizes the analysis of data of the 120 digit series with the **chi-square goodness-of-fit test**. The first column of the table lists 17 gap-length categories, which correspond to the 17 cells/categories in the chi-square table. It should be noted that the grouping of gaps into 17 categories is arbitrary. It is unlikely (although not impossible) that an alternative grouping format (i.e., a fewer or greater number of categories) will yield a substantially different

result for the chi-square analysis. Each row in Table 10.2 lists in Column 2 the observed number of gaps in the data with lengths that correspond to the values listed in the first column of that row. The expected number of gaps for the lengths listed are noted in Column 3, followed in parenthesis by the probability of obtaining gap values of the designated lengths. The latter probabilities were obtained by adding up the probability values for each of the gap lengths specified in a given row. Thus, the value .271 in the first row is the result of adding the values .1, .09, and .081, which are the values computed above (using the equation $P(r) = (.1)(.9)^r$) for the gap lengths 0, 1, and 2. The expected frequency in each row is computed by multiplying the expected row probability ($P(r)$) by 110 (which is the total number of gaps). Thus, in the case of the first row, $(110)(.271) = 29.81$.

Table 10.2 Summary of Chi-Square Analysis for Gap Test

Cell/Gap Length	Observed number of gaps (<i>O</i>)	Expected number of gaps (<i>E</i>) & (<i>P</i> (<i>r</i>))	$\frac{(O - E)^2}{E}$
0-2	18	29.81 (.271)	4.68
3-5	21	21.67 (.197)	.02
6-8	25	15.84 (.144)	5.30
9-11	15	11.55 (.105)	1.03
12-14	13	8.36 (.076)	2.58
15-17	6	6.27 (.057)	.01
18-20	5	4.51 (.041)	.05
21-23	2	3.30 (.030)	.51
24-26	3	2.31 (.021)	.21
27-29	1	1.76 (.016)	.33
30-32	0	1.21 (.011)	1.21
33-35	0	.99 (.009)	.99
36-38	0	.66 (.006)	.66
39-41	1	.44 (.004)	.71
42-44	0	.33 (.003)	.33
45-47	0	.33 (.003)	.33
48-50	0	.33 (.003)	.33
Sums	110	110	$\chi^2 = 19.28$

The degrees of freedom for the chi-square table equals 16, since it is one less than the number of cells (which equals 17). In order to reject the null hypothesis, and thus conclude that the distribution is not random, it is required that the computed value of chi-square is equal to or greater than the tabled critical value at the prespecified level of significance. Employing Table A4 for $df = 16$, $\chi^2_{.05} = 26.30$ and $\chi^2_{.01} = 32.00$. Since the obtained value $\chi^2 = 19.28$ is less than $\chi^2_{.05} = 26.30$, the null hypothesis is retained. Thus, the data are consistent with the series being random. Note, however, that the results of the above **gap test** are not consistent with the **gap test** analysis conducted previously with the **single-sample *z* test** and the **single-sample chi-square test for a population variance** (on the gap values of the mean and variance for the digit 0). It is, however, consistent with the **frequency test** on the same series of numbers, which also did not find evidence of nonrandomness.

Test 10d: The poker test Described in Banks and Carson (1984), Gruenberger and Jaffray (1965), Knuth (1969, 1981, 1997), Phillips *et al.* (1976), and Schmidt and Taylor (1970), the **poker test** conceptualizes a series of digits as a set of hands in the game of poker. Starting with the first five digits in a series of n digits, the five digits are considered as the initial poker hand.

In the analysis to be conducted, flushes are not possible, straights will not be employed, but five of a kind can occur. The analysis is repeated, employing as the second hand digits 6 through 10, and then as the third hand digits 11 through 15, and so on.¹¹ The **chi-square goodness-of-fit test** can be employed to evaluate the results of the test by comparing the observed frequencies for each of the possible hands with their theoretical/expected frequencies. Within the framework of tests of randomness that have been developed, the **poker test** is among the most stringent. Series of digits that are able to meet the criteria of other tests of randomness will often fail the **poker test**.

The same 120 digit series that was evaluated earlier with the **frequency test** and the **gap test** will be employed to illustrate the **poker test**. Each of the seven possible poker hands is listed, followed in parenthesis by a five digit hand illustrating it, as well as the probability of obtaining that hand: a) **All five digits different** (12345; $p = .3024$); b) **One pair** (11234; $p = .5040$); c) **Two pair** (11223; $p = .1080$); d) **Three of a kind** (11123; $p = .0720$); d) **Four of a kind** (11112; $p = .0045$); e) **Five of a kind** (11111; $p = .0001$); f) **Full house** (11122; $p = .0090$).¹² Table 10.3 summarizes the chi-square analysis of the data for the 120 digit series. The latter series yields only 24 poker hands, since $120/5 = 24$. Although, in reality, a much larger number of hands should be employed in using the **poker test** to assess randomness, for purposes of demonstration we will employ the 24 available hands. In Table 10.3, the expected number of observations for each type of hand was computed by multiplying the total number of hands (24) by the probability of that hand occurring. Thus, in the case the hand **All different**, the expected probability of 7.2576 was obtained as follows: $(24)(.3024) = 7.2576$.

Table 10.3 Summary of Chi-Square Analysis for Poker Test

Cell/Poker Hand	Observed number of hands (O)	Expected number of hands (E)	$\frac{(O - E)^2}{E}$
All different	13	7.2576	4.54
One pair	9	12.096	.79
Two pair	0	2.592	2.59
Three of a kind	2	1.728	.04
Four of a kind	0	.108	.11
Five of a kind	0	.0024	.00
Full house	0	.216	.22
Sums	24	24	$\chi^2 = 8.29$

The degrees of freedom for the chi-square table equals 6, since it is one less than the number of cells/categories (which equals 7). In order to reject the null hypothesis, and thus conclude that the distribution is not random, it is required that the computed value of chi-square is equal to or greater than the tabled critical value at the prespecified level of significance. Employing Table A4 for $df = 6$, $\chi^2_{.05} = 12.59$ and $\chi^2_{.01} = 16.81$. Since the obtained value $\chi^2 = 8.29$ is less than $\chi^2_{.05} = 12.59$, the null hypothesis is retained. Thus, the data are consistent with the series being random.

Test 10e: The maximum test Described in Gruenberger and Jaffray (1965), the **maximum test** evaluates strings of three consecutive digits and records the number of cases in which the middle digit is higher than either of the outside two digits (e.g., in the string 152, the 5 is larger than the 1 and 2). Gruenberger and Jaffray (1965) note that the likelihood of the latter occurring is .285. The **binomial sign test for a single sample** can be employed to evaluate the data, with n representing the total number of three digit strings analyzed in a sequence, and $\pi_1 = .285$ and

$\pi_2 = .715$, respectively, representing the likelihood of a **hit** versus a **miss** (where a **hit** is the middle digit being greater than the two outside digits).

The same series of 120 digits that have been evaluated with the other tests described in this section will now be evaluated with the **maximum test**. Beginning with the first digit and moving sequentially, 40 three-digit strings can be demarcated. Thus, the first string in the series which consists of the digits 893 is a hit, since the middle digit 9 is greater than the two outside digits 8 and 3. The second string 723 is a miss, since the middle digit 2 is not higher than both of the outside digits. Altogether, in 10 of the 40 strings ($p = 10/40 = .225$) the middle digit is larger than the two outside digits. The expected number of strings where the middle digit will be higher than the outside digit is $\mu = (\pi_1)(n) = (.285)(40) = 11.4$. Employing Equation 9.7, (the normal approximation the **binomial sign test for a single sample**), the value $z = -.49$ is computed. Equation 9.9, the continuity-corrected equation, yields the value $z = -.32$. The negative sign for the z values indicates that the observed number of strings is less than the expected number of strings.

$$z = \frac{x - n\pi_1}{\sqrt{n\pi_1\pi_2}} = \frac{10 - 11.4}{\sqrt{(40)(.285)(.715)}} = -.49$$

Since the absolute values $z = .49$ and $z = .32$ are lower than the tabled critical two-tailed value $z_{.05} = 1.96$ and the tabled critical one-tailed value $z_{.05} = 1.65$, the null hypothesis cannot be rejected, regardless of which alternative hypothesis is employed. The observed value $x = 10$ is well within chance expectation. Thus, we cannot conclude that the series is not random.

With the exception of the **gap test** that was conducted on the mean and variance for the digit 0, the 120 digit series passed all of the other tests of randomness (i.e., the **frequency test**, the **gap test for gap lengths for the entire distribution**, the **poker test**, and the **maximum test**). Note that the tests thus far described in this section are employed, for the most part, to evaluate series that are comprised of single digit integers and/or discrete data. The next test that will be described is designed to evaluate continuous data (i.e., values that are not necessarily whole numbers).

Test 10f: The mean square successive difference test (The reader should note that this test evaluates interval/ratio data.) Attributed to Bellinson *et al.* (1941) and von Neumann (1941) and described in Bennett and Franklin (1954), Chou (1989), and Zar (1999), the **mean square successive difference test** contrasts the mean of the squares of the differences of $(n - 1)$ successive differences in a series of n numbers with the variance of the n numbers. Within the framework of the test, the mean of the squares of the successive differences is conceptualized as an alternative measure of variance that is contrasted with the estimated population variance (which is computed with Equation I.5). The **mean square successive difference test** can be employed to evaluate whether or not a sequence of continuous interval/ratio scores is random. Zar (1999, p. 586) notes that an assumption of the latter test is that the data are derived from a normally distributed population.

The **mean square successive difference test** will be employed to evaluate Example 10.2 (which employs the same data as Example 10.5), which was previously evaluated with the **runs test for serial randomness (Test 10a)**. The serial distribution of the 21 scores for Example 10.2 is presented below.

1.90, 1.99, 2.00, 1.78, 1.77, 1.76, 1.98, 1.90, 1.65, 1.76, 2.01, 1.78, 1.99, 1.76, 1.94, 1.78, 1.67, 1.87, 1.91, 1.91, 1.89

The initial value that is computed in conducting the **mean square successive difference test** is the estimated population variance. Employing Equation I.5, the latter value is computed to be $\bar{s}^2 = .0122$ for the $n = 21$ scores in the series (the mean score in the series is $\bar{X} = 1.857$). Equation 10.8 is now employed to compute the **mean of the squares of the successive differences** (more specifically, the unbiased estimate of that value in the population). The latter value will be represented by the symbol \bar{s}_{ms}^2 .

$$\bar{s}_{ms}^2 = \frac{\sum_{i=1}^{n-1} (X_{i+1} - X_i)^2}{2(n-1)} \quad (\text{Equation 10.8})$$

The numerator of Equation 10.8 indicates that each score in the series is subtracted from the score that comes after it, each of the difference scores is squared, and the squared difference scores are summed. The sum of the squared difference scores is divided by $2(n-1)$, yielding the value of \bar{s}_{ms}^2 . The computation of the value $\bar{s}_{ms}^2 = .0128$ is demonstrated below.

$$\bar{s}_{ms}^2 = \frac{(1.99 - 1.90)^2 + (2.00 - 1.99)^2 + \dots + (1.91 - 1.91)^2 + (1.89 - 1.91)^2}{2(21 - 1)} = \frac{.5107}{40} = .0128$$

Equation 10.9 is employed to compute the test statistic, which Young (1941) designated as C . Employing the latter equation, the value $C = -.049$ is computed. Note that the value of C will be positive when $\bar{s}_{ms}^2 < \bar{s}^2$, negative when $\bar{s}_{ms}^2 > \bar{s}^2$, and equal to 0 when the two values are equal.

$$C = 1 - \frac{\bar{s}_{ms}^2}{\bar{s}^2} = 1 - \frac{.0128}{.0122} = -.049 \quad (\text{Equation 10.9})$$

In order to reject the null hypothesis and conclude that the distribution is nonrandom, the absolute value of C must be equal to or greater than the tabled critical value of the C statistic at the prespecified level of significance. A large absolute C value indicates there is a large discrepancy between the values \bar{s}^2 and \bar{s}_{ms}^2 . A table of critical values can be found in Zar (1999), who developed his table based on the work of Young (1941). Another table of the sampling distribution for this test (although not C values) was derived by Hart (1942), and can be found in Bennett and Franklin (1954). The computed absolute value $C = .049$ is less than Zar's (1999) tabled critical values $C_{.05} = .343$ and $C_{.01} = .470$. We thus retain the null hypothesis. In other words, the evidence does not indicate the distribution is not random.

In lieu of the exact table for the sampling distribution of C , we will employ a large sample normal approximation for the C statistic which is computed with Equation 10.10. Employing the latter equation, the value $z = -.24$ is computed.

$$z = \frac{C}{\sqrt{\frac{n-2}{n^2-1}}} = \frac{-.049}{\sqrt{\frac{21-2}{(21)^2-1}}} = -.24 \quad (\text{Equation 10.10})$$

Zar (1999) notes that one-tailed probabilities should be employed for the above analysis. To reject the null hypothesis and conclude that the distribution is nonrandom, the absolute value of z must be equal to or greater than the tabled critical value at the prespecified level of significance. Since the absolute value $z = .24$ is less than the tabled critical one-tailed value $z_{.05} = 1.65$, the null hypothesis cannot be rejected. Thus, the evidence does not indicate the

distribution is nonrandom. This is consistent with the conclusion that was reached when the same set of data was evaluated with the **runs test for serial randomness**.

Additional tests of randomness

1) **Autocorrelation** (also known as **serial correlation**) This procedure, which is discussed in detail in Section VII of the **Pearson product-moment correlation coefficient (Test 28)**, can be employed with series in which, in each trial, there are two or more possible categorical outcomes, or with continuous serial data (such as the data that were evaluated with the **runs test for serial randomness** and the **mean square successive difference test**). Within the framework of autocorrelation, one can conclude that a series is random if the correlation coefficient between successive numbers in the series is equal to zero. The **Durbin–Watson test** (1950, 1951, 1971) is one of a number of procedures that are employed for autocorrelation. The latter test is described in sources such as Chou (1989), Montgomery and Peck (1992), and Netter *et al.* (1988).

2) **The coupon collector's test** The **coupon collector's test** evaluates the number of digits required to make a complete set, which consists of all the integer values 1 to k . Mosteller (1965, p. 15) notes that in a random series, the average number of digits required (i.e., the expected value) to obtain a set that includes all k digits can be computed through use of the harmonic series $k[1/k + 1/(k-1) + 1/(k-2) + \dots + 1/2 + 1]$. Thus, if the integers 1 through 5 are employed in a series of random numbers, the expected number of trials that will be required to have a set that includes all five digits is $5(1/5 + 1/4 + 1/3 + 1/2 + 1) = 11.42$. The average number of digits can also be approximated quite accurately by employing the following equation: $k \ln k + .577k + 1/2$. When the latter equation is solved for $k = 5$ digits, it results in the value 11.43 (i.e., $5 \ln 5 + (.577)(5) + 1/2 = 11.43$). Within the framework of the **coupon collector's test**, inferential statistical procedures can be employed to do the following: a) Employ the **single-sample z test** to contrast the predicted/expected average number of digits (based on the equation noted above) with the observed average number of digits required for all of the complete sets comprised of k digits in the series; and b) Employ the **chi-square goodness-of-fit test** to evaluate the expected versus observed frequencies for categories that represent different values for the number of digits required to comprise a full set of k digits in the series. The algorithm for the **coupon collector's test** for computing expected probabilities (required for computing the expected frequencies) is described in Knuth (1969, 1981, 1997).

3) **The serial test** The **serial test** evaluates the occurrence of each two-digit combination ranging from 00 to kk , where k is the largest digit that can occur in the series. The **serial test** which can be generalized to groups consisting of combinations of three or more digits is described in more detail in Emshoff and Sisson (1970).

4) **The d^2 test of random numbers** Described in Gruenberger and Jaffray (1965), the **d^2 test of random numbers** conceptualizes random numbers as coordinates on a graph, and addresses the following question: If two points are chosen at random within a one unit square grid, what is the likelihood that the distance between the two points is greater than a specific value (e.g., that the value of d is greater than .5 and thus d^2 is greater than .25)? The **d^2 test of random numbers** is a stringent test that can be employed to evaluate random numbers that are in the range 0 to 1, since each point is represented by two numbers that fall in the latter range of values.

5) **Tests of trend analysis/time series analysis** Economists often refer to a set of observations that are measured over a period of time as a **time series**. The pattern of the data in a time series may be random or may instead be characterized by patterns or trends. **Trend analysis** and **time series analysis** are terms that are used to describe a variety of statistical procedures (such as those that have been described in this section) which are employed for analyzing such data. Among the other tests that are used for trend analysis that can be employed to identify a

nonrandom series is the **Cox–Stuart test for trend** (developed by Cox and Stuart (1955) and described in Conover (1999) and Daniel (1988)), which is a modification of the **binomial sign test for a single sample**. Other tests of time series and trend analysis are commonly described in books on business and economic statistics (e.g., Chou (1989), Hoel and Jessen (1982), Montgomery and Peck (1992), and Netter *et al.* (1988)).

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Endnotes

1. An alternate definition of randomness employed by some sources is that in a random series, each of k possible alternatives is equally likely to occur on any trial, and that the outcome on each trial is independent of the outcome on any other trial. The problem with the latter definition is that it cannot be applied to a series in which on each trial there are two or more alternatives which do not have a equal likelihood of occurring (the stipulation regarding independence does, however, also apply to a series involving alternatives that do not have an equal likelihood of occurring on each trial). In point of fact, it is possible to apply the concept of randomness to a series in which $\pi_1 \neq \pi_2$. To illustrate the latter, consider the following example. Assume we have a series consisting of N trials involving a binomially distributed variable for which there are two possible outcomes **A** and **B**. The theoretical

probabilities in the underlying population for each of the outcomes are $\pi_A = .75$ and $\pi_B = .25$. If a series involving the two alternatives is in fact random, on each trial the respective likelihoods of alternative **A** versus alternative **B** occurring will not be $\pi_A = \pi_B = .5$, but instead will be $\pi_A = .75$ and $\pi_B = .25$. If such a series is random it is expected that alternative **A** will occur approximately 75% of the time and alternative **B** will occur approximately 25% of the time. However, it is important to note that one cannot conclude that the above series is random purely on the basis of the relative frequencies of the two alternatives. To illustrate this, consider the following series consisting of 28 trials which is characterized by the presence of an invariant pattern: **AAABAAABAAABAAABAAABAAABAAAB**. If one is attempting to predict the outcome on the 29th trial, and if, in fact, the periodicity of the pattern that is depicted is invariant, the likelihood that alternative **A** will occur on the next trial is not .75, but is, in fact, 1. This is the case, since the occurrence of events in the series can be summarized by the simple algorithm that the series is comprised of 4 trial cycles, and within each cycle alternative **A** occurs on the first 3 trials and alternative **B** on the fourth trial. The point to be made here is that it is entirely possible to have a random series, even if each of the alternatives is not equally likely to occur on every trial. However, if the occurrence of the alternatives is consistent with their theoretical frequencies, the latter in and of itself does not insure that the series is random.

2. It should be pointed out that, in actuality, each of the three series depicted in [Figure 10.1](#) has an equal likelihood of occurring. However, in most instances where a consistent pattern is present that persists over a large number of trials, such a pattern is more likely to be attributed to a nonrandom factor than it is to chance.
3. The computation of the values in [Table A8](#) is based on the following logic. If a series consists of N trials and alternative 1 occurs n_1 times and alternative 2 occurs n_2 times, the number of possible combinations involving alternative 1 occurring n_1 times and alternative 2 occurring n_2 times will be $\binom{N}{n_1} = N!/(n_1!n_2!)$. Thus, if a coin is tossed $N = 4$ times, since $\binom{4}{2} = 4!/(2! 2!) = 6$, there will be 6 possible ways of obtaining $n_1 = 2$ Heads and $n_2 = 2$ Tails. Specifically, the 6 ways of obtaining 2 Heads and 2 Tails are: HHTT, TTHH, THHT, HTTH, THTH, HTHT. Each of the 6 aforementioned sequences constitutes a series, and the likelihood of each of the series occurring is equal. The two series HHTT and TTHH are comprised of 2 runs, the two series THHT and HTTH are comprised of 3 runs, and the two series THTH and HTHT are comprised of 4 runs. Thus, the likelihood of observing 2 runs will equal $2/6 = .33$, the likelihood of observing 3 runs will equal $2/6 = .33$, and the likelihood of observing 4 runs will equal $2/6 = .33$. The likelihood of observing 3 or more runs will equal .67, and the likelihood of observing 2 or more runs will equal 1. A thorough discussion of the derivation of the sampling distribution for the **single-sample runs test**, which is attributed in some sources to Wald and Wolfowitz (1940), is described in Hogg and Tanis (1988).
4. Some of the cells in [Table A8](#) only list a lower limit. For the sample sizes in question, there is no maximum number of runs (upper limit) that will allow the null hypothesis to be rejected.
5. A general discussion of the correction for continuity can be found under the **Wilcoxon signed-ranks test (Test 6)**. The reader should take note of the fact that the correction for

continuity described in this section is intended to provide a more conservative test of the null hypothesis (i.e., make it more difficult to reject). However, when the absolute value of the numerator of Equation 10.1 is equal to or very close to zero, the z value computed with Equation 10.2 will be further removed from zero than the z value computed with Equation 10.1. Since the continuity-corrected z value will be extremely close to zero, this result is of no practical consequence (i.e., the null hypothesis will still be retained). Zar (1999, p. 493), however, notes that in actuality the correction for continuity should not be applied if it increases rather than decreases the absolute value of the test statistic. This observation regarding the correction for continuity can be generalized to the continuity-correction described in the book for other nonparametric tests.

6. The term Monte Carlo derives from the fact that Ulam had an uncle with a predilection for gambling who often frequented the casinos at **Monte Carlo**.
7. The application of the **single-sample runs test** to a design involving two independent samples is described in Siegel (1956) under the **Wald–Wolfowitz (1940) runs test**.
8. A number is prime if it has no divisors except for itself and the value 1. In other words, if a prime number is divided by any number except itself or 1, it will yield a remainder.
9. The author is indebted to Theodore Sheskin for providing some of the reference material employed in this section.
10. Although Equation 10.2 (the continuity-corrected equation for the **single-sample runs test**) yields a slightly smaller absolute z value for this example and the example to follow, it leads to identical conclusions with respect to the null hypothesis.
11. Gruenberger and Jaffray (1965) note that an even more stringent variant of the poker test employs digits 2 through 6 as the second hand, digits 3 through 7 as the third hand, digits 4 through 8 as the fourth hand, and so on. The analysis is carried on until the end of the series (which will be the point at which a five-digit hand is no longer possible). The total of $(n - 4)$ possible hands can be evaluated with the **chi-square goodness-of-fit test**. However, since within the format just described the hands are not actually independent of one another (because they contain overlapping data), the assumption of independence for the **chi-square goodness-of-fit test** is violated.
12. a) Phillips *et al.* (1976), and Schmidt and Taylor (1970) describe the computation of the probabilities that are listed for the **poker test** for a **five digit hand**; b) Although it is generally employed with groups of five digits, the **poker test** can be applied to groups that consist of more or less than five digits. The poker test probabilities (for $k = 10$ digits) for a **four digit hand** (Schmidt and Taylor (1970)) and a **three digit hand** (Banks and Carson (1984)), along with a sample hand, are as follows: *Four digit hand: All four digits different* (1234; $p = .504$); *One pair* (1123; $p = .432$); *Two pair* (1122; $p = .027$); *Three of a kind* (1112; $p = .036$); *Four of a kind* (1111; $p = .001$). *Three digit hand: All three digits different* (123; $p = .72$); *One pair* (112; $p = .27$); *Three of a kind* (111; $p = .01$).

Inferential Statistical Tests Employed with Two Independent Samples (and Related Measures of Association/Correlation)

Test 11: The t Test for Two Independent Samples

Test 12: The Mann–Whitney U Test

**Test 13: The Kolmogorov-Smirnov Test for Two
Independent Samples**

Test 14: The Siegel-Tukey Test for Equal Variability

Test 15: The Moses Test for Equal Variability

Test 16: The Chi-Square Test for $r \times c$ Tables

Test 11

The t Test for Two Independent Samples (Parametric Test Employed with Interval/Ratio Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test Do two independent samples represent two populations with different mean values?¹

Relevant background information on test The t test for two independent samples, which is employed in a hypothesis testing situation involving two independent samples, is one of a number of inferential statistical tests that are based on the t distribution (which is discussed in detail under the **single-sample t test (Test 2)**). Two or more samples are independent of one another if each of the samples is comprised of different subjects.² In addition to being referred to as an **independent samples design**, a design involving two or more independent samples is also referred to as a **between-subjects design**, a **between-groups design**, and a **randomized-groups design**. In order to eliminate the possibility of **confounding** in an **independent samples design**, each subject should be randomly assigned to one of the k (where $k \geq 2$) experimental conditions.

In conducting the t test for two independent samples, the two sample means (represented by the notations \bar{X}_1 and \bar{X}_2) are employed to estimate the values of the means of the populations (μ_1 and μ_2) from which the samples are derived. If the result of the t test for two independent samples is significant, it indicates the researcher can conclude there is a high likelihood that the samples represent populations with different mean values. It should be noted that the t test for two independent samples is the appropriate test to employ for contrasting the means of two independent samples when the values of the underlying population variances are unknown. In instances where the latter two values are known, the appropriate test to employ is the z test for two independent samples (Test 11d), which is described in Section VI.

The t test for two independent samples is employed with interval/ratio data, and is based on the following assumptions: a) Each sample has been randomly selected from the population it represents; b) The distribution of data in the underlying population from which each of the samples is derived is normal; and c) The third assumption, which is referred to as the **homogeneity of variance** assumption, states that the variance of the underlying population represented by Sample 1 is equal to the variance of the underlying population represented by Sample 2 (i.e., $\sigma_1^2 = \sigma_2^2$). The homogeneity of variance assumption is discussed in detail in Section VI. If any of the aforementioned assumptions are saliently violated, the reliability of the t test statistic may be compromised.

II. Example

Example 11.1 *In order to assess the efficacy of a new antidepressant drug, ten clinically depressed patients are randomly assigned to one of two groups. Five patients are assigned to Group 1, which is administered the antidepressant drug for a period of six months. The other five*

patients are assigned to Group 2, which is administered a placebo during the same six-month period. Assume that prior to introducing the experimental treatments, the experimenter confirmed that the level of depression in the two groups was equal. After six months elapse all ten subjects are rated by a psychiatrist (who is blind with respect to a subject's experimental condition) on their level of depression. The psychiatrist's depression ratings for the five subjects in each group follow (the higher the rating the more depressed a subject): **Group 1:** 11, 1, 0, 2, 0; **Group 2:** 11, 11, 5, 8, 4. Do the data indicate that the antidepressant drug is effective?

III. Null versus Alternative Hypotheses

Null hypothesis

$$H_0: \mu_1 = \mu_2$$

(The mean of the population Group 1 represents equals the mean of the population Group 2 represents.)

Alternative hypothesis

$$H_1: \mu_1 \neq \mu_2$$

(The mean of the population Group 1 represents does not equal the mean of the population Group 2 represents. This is a **nondirectional alternative hypothesis** and it is evaluated with a **two-tailed test**. In order to be supported, the absolute value of t must be equal to or greater than the tabled critical two-tailed t value at the prespecified level of significance. Thus, either a significant positive t value or a significant negative t value will provide support for this alternative hypothesis.)

or

$$H_1: \mu_1 > \mu_2$$

(The mean of the population Group 1 represents is greater than the mean of the population Group 2 represents. This is a **directional alternative hypothesis** and it is evaluated with a **one-tailed test**. It will only be supported if the sign of t is positive, and the absolute value of t is equal to or greater than the tabled critical one-tailed t value at the prespecified level of significance.)

or

$$H_1: \mu_1 < \mu_2$$

(The mean of the population Group 1 represents is less than the mean of the population Group 2 represents. This is a **directional alternative hypothesis** and it is evaluated with a **one-tailed test**. It will only be supported if the sign of t is negative, and the absolute value of t is equal to or greater than the tabled critical one-tailed t value at the prespecified level of significance.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis is rejected.³

IV. Test Computations

The data for Example 11.1 are summarized in [Table 11.1](#). In the example there are $n_1 = 5$ subjects in Group 1 and $n_2 = 5$ subjects in Group 2. In [Table 11.1](#) each subject is identified by a two digit number. The first digit before the comma indicates the subject's number within the group, and the second digit indicates the group identification number. Thus, Subject i, j is the i^{th} subject in Group j . The scores of the 10 subjects are listed in the columns of [Table 11.1](#) labelled X_1 and X_2 . The adjacent columns labelled X_1^2 and X_2^2 contain the square of each subject's score.

Table 11.1 Data for Example 11.1

	Group 1			Group 2	
	X_1	X_1^2		X_2	X_2^2
Subject 1,1	11	121	Subject 1,2	11	121
Subject 2,1	1	1	Subject 2,2	11	121
Subject 3,1	0	0	Subject 3,2	5	25
Subject 4,1	2	4	Subject 4,2	8	64
Subject 5,1	0	0	Subject 5,2	4	16
	$\Sigma X_1 = 14$	$\Sigma X_1^2 = 126$		$\Sigma X_2 = 39$	$\Sigma X_2^2 = 347$

Employing Equations I.1 and I.5, the mean and estimated population variance for each sample is computed below.

$$\bar{X}_1 = \frac{\Sigma X_1}{n_1} = \frac{14}{5} = 2.8 \quad \hat{s}_1^2 = \frac{\Sigma X_1^2 - \frac{(\Sigma X_1)^2}{n_1}}{n_1 - 1} = \frac{126 - \frac{(14)^2}{5}}{5 - 1} = 21.7$$

$$\bar{X}_2 = \frac{\Sigma X_2}{n_2} = \frac{39}{5} = 7.8 \quad \hat{s}_2^2 = \frac{\Sigma X_2^2 - \frac{(\Sigma X_2)^2}{n_2}}{n_2 - 1} = \frac{347 - \frac{(39)^2}{5}}{5 - 1} = 10.7$$

When there are an **equal number of subjects** in each sample, Equation 11.1 can be employed to compute the test statistic for the ***t* test for two independent samples**.⁴

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{\hat{s}_1^2}{n_1} + \frac{\hat{s}_2^2}{n_2}}} \quad (\text{Equation 11.1})$$

Employing Equation 11.1, the value $t = -1.96$ is computed.

$$t = \frac{2.8 - 7.8}{\sqrt{\frac{21.7}{5} + \frac{10.7}{5}}} = \frac{-5}{2.55} = -1.96$$

Equation 11.2 is an alternative way of expressing Equation 11.1.

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{s_{\bar{X}_1}^2 + s_{\bar{X}_2}^2}} \quad (\text{Equation 11.2})$$

Note that in Equation 11.2, the values $s_{\bar{X}_1}^2$ and $s_{\bar{X}_2}^2$ represent the squares of the **standard error of the means** of the two groups. Employing the square of the value computed with Equation 2.2 (presented in Section IV of the **single-sample *t* test**), the squared standard error of the means of the two samples are computed: $s_{\bar{X}_1}^2 = \hat{s}_1^2/n_1 = 21.7/5 = 4.34$ and $s_{\bar{X}_2}^2 = \hat{s}_2^2/n_2 = 10.7/5 = 2.14$. When the values $s_{\bar{X}_1}^2 = 4.34$ and $s_{\bar{X}_2}^2 = 2.14$ are substituted in Equation 11.2, they yield the value $t = -1.96$: $t = (2.8 - 7.8)/\sqrt{4.34 + 2.14} = -1.96$.

The reader should take note of the fact that the values \bar{s}_1^2 , \bar{s}_2^2 , $s_{\bar{X}_1}^2$, and $s_{\bar{X}_2}^2$ (all of which are estimates of either the variance of a population or the variance of a sampling distribution) can never be negative numbers. If a negative value is obtained for any of the aforementioned values, it indicates a computational error has been made.

Equation 11.3 is a general equation for the ***t* test for two independent samples** that can be employed for both **equal and unequal samples sizes** (when $n_1 = n_2$, Equation 11.3 becomes equivalent to Equations 11.1/11.2).

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\left[\frac{(n_1 - 1)\bar{s}_1^2 + (n_2 - 1)\bar{s}_2^2}{n_1 + n_2 - 2} \right] \left[\frac{1}{n_1} + \frac{1}{n_2} \right]}} \quad \text{(Equation 11.3)}$$

In the case of Example 11.1, Equation 11.3 yields the identical value $t = -1.96$ obtained with Equations 11.1/11.2.

$$t = \frac{2.8 - 7.8}{\sqrt{\left[\frac{(5 - 1)(21.7) + (5 - 1)(10.7)}{5 + 5 - 2} \right] \left[\frac{1}{5} + \frac{1}{5} \right]}} = -1.96$$

The left element inside the radical of the denominator of Equation 11.3 represents a weighted average (based on the values of n_1 and n_2) of the estimated population variances of the two groups. This weighted average is referred to as a **pooled variance estimate**, represented by the notation \bar{s}_p^2 .⁵ Thus: $\bar{s}_p^2 = [(n_1 - 1)\bar{s}_1^2 + (n_2 - 1)\bar{s}_2^2] / (n_1 + n_2 - 2)$. It should be noted that if Equations 11.1/11.2 are applied to data where $n_1 \neq n_2$, the absolute value of t will be slightly higher than the value computed with Equation 11.3. Thus, use of Equations 11.1/11.2 when $n_1 \neq n_2$ makes it easier to reject the null hypothesis, and consequently inflates the likelihood of committing a Type I error. The application of Equations 11.1–11.3 to a set of data when $n_1 \neq n_2$ is illustrated in Section VII.

Regardless of which equation is employed, the denominator of the ***t* test for two independent samples** is referred to as the **standard error of the difference**. This latter value, which can be summarized with the notation $s_{\bar{X}_1 - \bar{X}_2}$, represents an estimated standard deviation of difference scores for two populations. Thus, in Example 11.1, $s_{\bar{X}_1 - \bar{X}_2} = 2.55$. If $s_{\bar{X}_1 - \bar{X}_2}$ is employed as the denominator of the equation for the ***t* test for two independent samples**, the equation can be written as follows: $t = (\bar{X}_1 - \bar{X}_2) / s_{\bar{X}_1 - \bar{X}_2}$.⁶

It should be noted that in some sources the numerator of Equations 11.1–11.3 is written as follows: $[(\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)]$. The latter notation is only necessary if in stating the null hypothesis, a researcher stipulates that the difference between μ_1 and μ_2 is some value other than zero. When the null hypothesis is $H_0: \mu_1 = \mu_2$, the value $(\mu_1 - \mu_2)$ reduces to zero, leaving the term $(\bar{X}_1 - \bar{X}_2)$ as the numerator of the t test equation. The application of the ***t* test for two independent samples** to a hypothesis testing situation in which a value other than zero is stipulated in the null hypothesis is illustrated with Example 11.2 in Section VI.

V. Interpretation of the Test Results

The obtained value $t = -1.96$ is evaluated with **Table A2 (Table of Student's *t* Distribution)** in the **Appendix**. The degrees of freedom for the ***t* test for two independent samples** are computed with Equation 11.4.⁷

$$df = n_1 + n_2 - 2 \quad (\text{Equation 11.4})$$

Employing Equation 11.4, the value $df = 5 + 5 - 2 = 8$ is computed. Thus, the tabled critical t values that are employed in evaluating the results of Example 11.1 are the values recorded in the cells of **Table A2** that fall in the row for $df = 8$, and the columns with probabilities that correspond to the two-tailed and one-tailed .05 and .01 values. (The protocol for employing **Table A2** is described in Section V of the **single-sample t test**.) The critical t values for $df = 8$ are summarized in **Table 11.2**.

Table 11.2 Tabled Critical .05 and .01 t Values $df = 8$

	$t_{.05}$	$t_{.01}$
Two-tailed values	2.31	3.36
One-tailed values	1.86	2.90

The following guidelines are employed in evaluating the null hypothesis for the **t test for two independent samples**.

a) If the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is employed, the null hypothesis can be rejected if the obtained absolute value of t is equal to or greater than the tabled critical two-tailed value at the prespecified level of significance.

b) If the directional alternative hypothesis $H_1: \mu_1 > \mu_2$ is employed, the null hypothesis can be rejected if the sign of t is positive, and the value of t is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

c) If the directional alternative hypothesis $H_1: \mu_1 < \mu_2$ is employed, the null hypothesis can be rejected if the sign of t is negative, and the absolute value of t is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

Employing the above guidelines, the null hypothesis can only be rejected (and only at the .05 level) if the directional alternative hypothesis $H_1: \mu_1 < \mu_2$ is employed. This is the case, since the obtained value $t = -1.96$ is a negative number, and the absolute value $t = 1.96$ is greater than the tabled critical one-tailed .05 value $t_{.05} = 1.86$. This outcome is consistent with the prediction that the group which receives the antidepressant will exhibit a lower level of depression than the placebo group. Note that the alternative hypothesis $H_1: \mu_1 < \mu_2$ is not supported at the .01 level, since the obtained absolute value $t = 1.96$ is less than the tabled critical one-tailed .01 value $t_{.01} = 2.90$.

The nondirectional alternative hypothesis $H_0: \mu_1 \neq \mu_2$ is not supported, since the obtained absolute value $t = 1.96$ is less than the tabled critical two-tailed .05 value $t_{.05} = 2.31$.

The directional alternative hypothesis $H_1: \mu_1 > \mu_2$ is not supported, since the obtained value $t = -1.96$ is a negative number. In order for the alternative hypothesis $H_1: \mu_1 > \mu_2$ to be supported, the computed value of t must be a positive number (as well as the fact that the absolute value of t must be equal to or greater than the tabled critical one-tailed value at the prespecified level of significance). It should be noted, that it is not likely the researcher would employ the latter alternative hypothesis, since it predicts that the placebo group will exhibit a lower level of depression than the group that receives the antidepressant.

A summary of the analysis of Example 11.1 with the **t test for two independent samples** follows: It can be concluded that the average depression rating for the group that receives the antidepressant medication is significantly less than the average depression rating for the placebo group. This conclusion can only be reached if the directional alternative hypothesis $H_1: \mu_1 < \mu_2$ is employed, and the prespecified level of significance is $\alpha = .05$. This result can be summarized as follows: $t(8) = 1.96, p < .05$.⁸

VI. Additional Analytical Procedures for the t Test for Two Independent Samples and/or Related Tests

1. The equation for the t test for two independent samples when a value for a difference other than zero is stated in the null hypothesis In some sources Equation 11.5 is presented as the equation for the t test for two independent samples.

$$t = \frac{(\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)}{s_{\bar{X}_1 - \bar{X}_2}} \quad (\text{Equation 11.5})$$

It is only necessary to employ Equation 11.5 if, in stating the null hypothesis, a researcher stipulates that the difference between μ_1 and μ_2 is some value other than zero. When the null hypothesis is $H_0: \mu_1 = \mu_2$ (which as noted previously can also be written as $H_0: \mu_1 - \mu_2 = 0$), the value of $(\mu_1 - \mu_2)$ reduces to zero, and thus what remains of the numerator in Equation 11.5 is $(\bar{X}_1 - \bar{X}_2)$, which constitutes the numerator of Equations 11.1–11.3. Example 11.2 will be employed to illustrate the use of Equation 11.5 in a hypothesis-testing situation in which some value other than zero is stipulated in the null hypothesis.

Example 11.2 *The Accusharp Battery Company claims that the hearing aid battery it manufactures has an average life span that is two hours longer than the average life span of a battery manufactured by the Keenair Battery Company. In order to evaluate the claim, an independent researcher measures the life span of five randomly selected batteries from the stock of each of the two companies, and obtains the following values: **Accusharp:** 10, 8, 10, 9, 11; **Keenair:** 8, 9, 8, 7, 9. Do the data support the claim of the Accusharp Company?*

Since the Accusharp Company (which will be designated as Group 1) specifically predicts that the life span of its battery is 2 hours longer, the null hypothesis can be stated as follows: $H_0: \mu_1 - \mu_2 = 2$. The alternative hypothesis if stated nondirectionally is $H_1: \mu_1 - \mu_2 \neq 2$. If the computed absolute value of t is equal to or greater than the tabled critical two-tailed t value at the prespecified level of significance, the nondirectional alternative hypothesis is supported. If stated directionally, the appropriate alternative hypothesis to employ is $H_1: \mu_1 - \mu_2 < 2$. The latter directional alternative hypothesis (which predicts a negative t value) is employed, since in order for the data to contradict the claim of the Accusharp Company (and thus reject the null hypothesis), the life span of the latter's battery can be any value that is less than 2 hours longer than that of the Keenair battery. The alternative hypothesis $H_1: \mu_1 - \mu_2 > 2$ (which is only supported with a positive t value) predicts that the superiority of the Accusharp battery is greater than 2 hours. If the latter alternative hypothesis is employed, the null hypothesis can only be rejected if the life span of the Accusharp battery is greater than 2 hours longer than that of the Keenair battery.

The analysis for Example 11.2 is summarized below.

$$\Sigma X_1 = 48 \quad \bar{X}_1 = \frac{48}{5} = 9.6 \quad \Sigma X_1^2 = 466$$

$$\Sigma X_2 = 41 \quad \bar{X}_2 = \frac{41}{5} = 8.2 \quad \Sigma X_2^2 = 339$$

$$\begin{aligned} s_1^2 &= \frac{466 - \frac{(48)^2}{5}}{5 - 1} = 1.3 & s_2^2 &= \frac{339 - \frac{(41)^2}{5}}{5 - 1} = .7 \\ t &= \frac{(9.6 - 8.2) - 2}{\sqrt{\frac{1.3}{5} + \frac{.7}{5}}} = \frac{-.6}{.63} = -.95 \end{aligned}$$

Since $df = 5 + 5 - 2 = 8$, the tabled critical values in Table 11.2 can be employed to evaluate the results of the analysis. Since the obtained absolute value $t = .95$ is less than the tabled critical two-tailed value $t_{.05} = 2.31$, the null hypothesis is retained. Thus, the non-directional alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 2$ is not supported. It is also true that the directional alternative hypothesis $H_1: \mu_1 - \mu_2 < 2$ is not supported. This is the case since although, as predicted, the sign of the computed t value is negative, the absolute value $t = .95$ is less than the tabled critical one-tailed value $t_{.05} = 1.86$. The nondirectional alternative hypothesis $H_1: \mu_1 - \mu_2 > 2$ is not supported, since in order for the latter directional alternative hypothesis to be supported, the sign of t must be positive, and the absolute value of t must be equal to or greater than tabled critical one-tailed value at the prespecified level of significance.

Thus, irrespective of whether a nondirectional or directional alternative hypothesis is employed, the data are consistent with the claim of the Accusharp company that it manufactures a battery that has a life span which is at least two hours longer than that of the Keenair battery. In other words, the obtained difference $(\bar{X}_1 - \bar{X}_2) = 1.4$ in the numerator of Equation 11.5 is not small enough to support the directional alternative hypothesis $H_1: \mu_1 - \mu_2 < 2$.

If $H_0: \mu_1 = \mu_2$ and $H_1: \mu_1 \neq \mu_2$ are employed as the null hypothesis and nondirectional alternative hypothesis for Example 11.2, analysis of the data yields the following result: $t = (9.6 - 8.2)/.63 = 2.22$. Since the obtained value $t = 2.22$ is less than the tabled critical two-tailed value $t_{.05} = 2.31$, the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is not supported at the .05 level. Thus, one cannot conclude that the life span of the Accusharp battery is significantly different than the life span of the Keenair battery. The directional alternative hypothesis $H_1: \mu_1 > \mu_2$ (which can also be written as $H_1: \mu_1 - \mu_2 > 0$) is supported at the .05 level, since $t = 2.22$ is a positive number that is larger than the tabled critical one-tailed value $t_{.05} = 1.86$. Thus, if the null hypothesis $H_0: \mu_1 = \mu_2$ and the directional alternative hypothesis $H_1: \mu_1 > \mu_2$ are employed, the researcher is able to conclude that the life span of the Accusharp battery is significantly longer than the life span of the Keenair battery.

The evaluation of Example 11.2 in this section reflects that fact that the conclusions one reaches can be affected by how a researcher states the null and alternative hypotheses. In the case of Example 11.2, the fact that the nondirectional alternative hypothesis $H_1: \mu_1 - \mu_2 \neq 2$ is not supported suggests that there is a two-hour difference in favor of Accustar (since the null hypothesis $H_0: \mu_1 - \mu_2 = 2$ is retained). Yet, if the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is employed, the fact that it is not supported suggests there is no difference between the two brands of batteries.

2. Test 11a: Hartley's F_{\max} test for homogeneity of variance/ F test for two population variances: Evaluation of the homogeneity of variance assumption of the t test for two independent samples It is noted in Section I that one assumption of the t test for two independent samples is **homogeneity of variance**. Specifically, the homogeneity of variance assumption evaluates whether there is evidence to indicate that an inequality exists between the variances of the populations represented by the two experimental samples. When the latter condition exists,

it is referred to as **heterogeneity of variance**. The null and alternative hypotheses employed in evaluating the homogeneity of variance assumption are as follows.

Null hypothesis $H_0: \sigma_1^2 = \sigma_2^2$

(The variance of the population Group 1 represents equals the variance of the population Group 2 represents.)

Alternative hypothesis $H_1: \sigma_1^2 \neq \sigma_2^2$

(The variance of the population Group 1 represents does not equal the variance of the population Group 2 represents. This is a **nondirectional alternative hypothesis** and it is evaluated with a **two-tailed test**. In evaluating the homogeneity of variance assumption for the **t test for two independent samples**, a nondirectional alternative hypothesis is always employed.)

One of a number of procedures that can be used to evaluate the homogeneity of variance hypothesis is **Hartley's F_{\max} test** (Hartley (1940,1950)), which can be employed with a design involving two or more independent samples.⁹ Although the **F_{\max} test** assumes an equal number of subjects per group, Kirk (1982, 1995) and Winer *et al.* (1991) among others note that if $n_1 \neq n_2$, but are approximately the same size, one can let the value of the larger sample size represent n when interpreting the F_{\max} test statistic. The latter sources, however, note that using the larger n will result in a slight increase in the Type I error rate for the F_{\max} test.

The test statistic for Hartley's F_{\max} test is computed with Equation 11.6.

$$F_{\max} = \frac{\hat{s}_L^2}{\hat{s}_S^2} \quad \text{(Equation 11.6)}$$

Where: \hat{s}_L^2 = The larger of the two estimated population variances
 \hat{s}_S^2 = The smaller of the two estimated population variances

Employing Equation 11.6 with the estimated population variances computed for Example 11.1, the value $F_{\max} = 2.03$ is computed. The reader should take note of the fact that the computed value for F_{\max} will always be a positive number that is greater than 1 (unless $\hat{s}_L^2 = \hat{s}_S^2$, in which case $F_{\max} = 1$).

$$F_{\max} = \frac{21.7}{10.7} = 2.03$$

The computed value $F_{\max} = 2.03$ is evaluated with **Table A9 (Table of the F_{\max} Distribution)** in the **Appendix**. The tabled critical values for the F_{\max} distribution are listed in reference to the values $(n - 1)$ and k , where n represents the number of subjects per group, and k represents the number of groups. In the case of Example 11.1, the value of $n = n_1 = n_2 = 5$. Thus, $n - 1 = 5 - 1 = 4$. Since there are two groups, $k = 2$.

In order to reject the null hypothesis and conclude that the homogeneity of variance assumption has been violated, the obtained F_{\max} value must be equal to or greater than the tabled critical value at the prespecified level of significance. All values listed in **Table A9** are two-tailed values. Inspection of **Table A9** indicates that for $n - 1 = 4$ and $k = 2$, $F_{\max_{.05}} = 9.6$ and $F_{\max_{.01}} = 23.2$. Since the obtained value $F_{\max} = 2.03$ is less than $F_{\max_{.05}} = 9.6$, the homogeneity of variance assumption is not violated — in other words the data do not suggest that the variances

of the populations represented by the two groups are unequal. Thus, the null hypothesis is retained.

There are a number of additional points that should be made with regard to the above analysis:

a) Some sources employ Equation 11.7 or Equation 11.8 in lieu of Equation 11.6 to evaluate the homogeneity of variance assumption. When Equation 11.8 is employed to contrast two variances, it is often referred to as an ***F* test for two population variances**.

$$F = \frac{\tilde{s}_L^2}{\tilde{s}_S^2} \quad (\text{Equation 11.7})$$

$$F = \frac{\tilde{s}_1^2}{\tilde{s}_2^2} \quad (\text{Equation 11.8})$$

Both Equations 11.7 and 11.8 compute an *F* ratio, which is based on the *F* distribution. Critical values for the latter distribution are presented in **Table A10 (Table of the *F* Distribution)** in the **Appendix**. The *F* distribution (which is discussed in greater detail under the **single-factor between-subjects analysis of variance (Test 21)**) is, in fact, the sampling distribution upon which the F_{\max} distribution is based. In **Table A10**, critical values are listed in reference to the number of degrees of freedom associated with the numerator and the denominator of the *F* ratio. In employing the *F* distribution in reference to Equation 11.7, the degrees of freedom for the numerator of the *F* ratio is $df_{\text{num}} = n_L - 1$ (where n_L represents the number of subjects in the group with the larger estimated population variance), and the degrees of freedom for the denominator is $df_{\text{den}} = n_S - 1$ (where n_S represents the number of subjects in the group with the smaller estimated population variance). The tabled $F_{.975}$ value is employed to evaluate a two-tailed alternative hypothesis at the .05 level, and the tabled $F_{.995}$ value is employed to evaluate it at the .01 level.¹⁰ The reason for employing the tabled $F_{.975}$ and $F_{.995}$ values instead of $F_{.95}$ (which in this analysis represents the two-tailed .10 value and the one-tailed .05 value) and $F_{.99}$ (which in this analysis represents the two-tailed .02 value and the one-tailed .01 value), is that both tails of the distribution are used in employing the *F* distribution to evaluate a hypothesis about two population variances. Thus, if one is conducting a two-tailed analysis with $\alpha = .05$, .025 (i.e., $.05/2 = .025$) represents the proportion of cases in the extreme left of the left tail of the *F* distribution, as well as the proportion of cases in the extreme right of the right tail of the distribution. With respect to a two-tailed analysis with $\alpha = .01$, .005 (i.e., $.01/2 = .005$) represents the proportion of cases in the extreme left of the left tail of the distribution, as well as the proportion of cases in the extreme right of the right tail of the distribution.

In point of fact, if $df_L = df_{\text{num}} = 4$ and $df_S = df_{\text{den}} = 4$ (which are the values employed in Example 11.1), the tabled critical two-tailed *F* values employed for $\alpha = .05$ and $\alpha = .01$ are $F_{.975} = 9.6$ and $F_{.995} = 23.15$. These are the same critical .05 and .01 values that are employed for the F_{\max} test.¹¹ Thus, Equation 11.7 employs the same critical values and yields an identical result to that obtained with Equation 11.6. It should be noted, however, that if $n_1 \neq n_2$, Equation 11.6 and Equation 11.7 will employ different critical values, since Equation 11.7 (which uses the value of *n* for each group in determining degrees of freedom) can accommodate unequal sample sizes.

When Group 1 has a larger estimated population variance than Group 2, everything that has been said with respect to Equation 11.7 applies to Equation 11.8. However, when $\tilde{s}_2^2 > \tilde{s}_1^2$, the value of *F* computed with Equation 11.8 will be less than 1. In such an instance, one can do either of the following: a) Designate the group with the larger variance as Group 1 and the group with

the smaller variance as Group 2. Upon doing this, divide the larger variance by the smaller variance (as is done in Equation 11.7), and thus obtain the same F value derived with Equation 11.7; or b) Use Equation 11.8, and employ the tabled critical $F_{.025}$ value to evaluate a two-tailed alternative hypothesis at the .05 level of significance, and the tabled critical $F_{.005}$ value to evaluate a two-tailed alternative hypothesis at the .01 level of significance.¹² In such a case, in order to be significant the computed F value must be equal to or less than the tabled critical $F_{.025}$ value (if $\alpha = .05$) or the tabled critical $F_{.005}$ value (if $\alpha = .01$). Both of the aforementioned methods will yield the same conclusions with respect to retaining or rejecting the null hypothesis at a given level of significance.

Equation 11.8 can also be used to test a directional alternative hypothesis concerning the relationship between two population variances. If a researcher specifically predicts that the variance of the population represented by Group 1 is larger than the variance of the population represented by Group 2 (i.e., $H_1: \sigma_1^2 > \sigma_2^2$), or that the variance of the population represented by Group 1 is smaller than the variance of the population represented by Group 2 (i.e., $H_1: \sigma_1^2 < \sigma_2^2$), a directional alternative hypothesis is evaluated. In such a case, the tabled critical one-tailed F value for $(n_1 - 1), (n_2 - 1)$ degrees of freedom at the prespecified level of significance is employed.

To illustrate the analysis of a one-tailed alternative hypothesis, let us assume that the alternative hypothesis $H_1: \sigma_1^2 > \sigma_2^2$ is evaluated. If $\alpha = .05$, in order for the result to be significant the computed value of F must be greater than 1. In addition, the tabled critical F value that is employed in evaluating the above alternative hypothesis is $F_{.95}$. To be significant, the obtained F value must be equal to or greater than the tabled critical $F_{.95}$ value. If $\alpha = .01$, the tabled critical F value that is employed in evaluating the alternative hypothesis is $F_{.99}$. To be significant, the obtained F value must be equal to or greater than the tabled critical $F_{.99}$ value.

Now let us assume that the alternative hypothesis being evaluated is $H_1: \sigma_1^2 < \sigma_2^2$. If $\alpha = .05$, in order for the result to be significant, the computed value of F must be less than 1. The tabled critical F value that is employed in evaluating the above alternative hypothesis is $F_{.05}$. To be significant, the obtained F value must be equal to or less than the tabled critical $F_{.05}$ value. If $\alpha = .01$, the tabled critical F value that is employed in evaluating the alternative hypothesis is $F_{.01}$. To be significant, the obtained F value must be equal to or less than the tabled critical $F_{.01}$ value.

If Equation 11.8 is employed with a one-tailed alternative hypothesis with reference to two groups consisting of five subjects per group (as is the case in Example 11.1), the following tabled critical values listed for $(n_1 - 1) = 4, (n_2 - 1) = 4$ are employed: a) If $\alpha = .05$, $F_{.95} = 6.39$, and $F_{.05} = .157$; and b) If $\alpha = .01$, $F_{.99} = 15.98$, and $F_{.01} = .063$.¹³ To illustrate this in a situation where an F value less than 1 is computed, assume for the moment that we employ the alternative hypothesis $H_1: \sigma_1^2 < \sigma_2^2$ for the two groups described in Example 11.1, and that the values of the two group variances are reversed — i.e., $\bar{s}_1^2 = 10.7$ and $\bar{s}_2^2 = 21.7$. Employing Equation 11.8 with this data, $F = 10.7/21.7 = .49$. The obtained value $F = .49$ is not significant, since to be significant, the computed value of F must be equal to or less than $F_{.05} = .157$.

It should be noted that when the general procedure discussed in this section is employed to evaluate the homogeneity of variance assumption with reference to Example 11.1, in order to reject the null hypothesis for $\alpha = .05$, the larger of the estimated population variances must be more than 9 times the magnitude of the smaller variance, and for $\alpha = .01$ the larger variance must be more than 23 times the magnitude of the smaller variance. Within the framework of the F_{\max} test, such a large discrepancy between the estimated population variances is tolerated when the number of subjects per group is small. Inspection of [Table A9](#) reveals that as sample size increases, the magnitude of the tabled critical F_{\max} values decreases. Thus, the larger the sample size, the smaller the difference between the variances that will be acceptable.

Two assumptions common to Equations 11.6–11.8 (i.e., all of the equations that can be employed to evaluate the homogeneity of variance assumption) are: a) Each sample has been randomly selected from the population it represents; and b) The distribution of data in the underlying population from which each of the samples is derived is normal. Violation of these assumptions can compromise the reliability of the F_{\max} test statistic, which many sources note is extremely sensitive to violation of the normality assumption. Various sources (e.g., Keppel (1991)) point out that when the F_{\max} test is employed to evaluate the homogeneity of variance hypothesis, it is not as powerful (i.e., likely to detect heterogeneity of variance when it is present) as some alternative but computationally more involved procedures. The consequence of not detecting heterogeneity of variance is that it increases the likelihood of committing a Type I error in conducting the ***t* test for two independent samples**. Additional discussion of the homogeneity of variance assumption and alternative procedures that can be used to evaluate it can be found in Section VI of the **single-factor between-subjects analysis of variance**.

In the event the homogeneity of variance assumption is violated, a number of different strategies (which yield similar but not identical results) are recommended with reference to conducting the ***t* test for two independent samples**. Since heterogeneity of variance increases the likelihood of committing a Type I error, all of the strategies that are recommended result in a more conservative *t* test (i.e., making it more difficult for the test to reject the null hypothesis). Such strategies compute either: a) An adjusted critical *t* value that is larger than the unadjusted critical *t* value; or b) An adjusted degrees of freedom value which is smaller than the value computed with Equation 11.4. By decreasing the degrees of freedom, a larger tabled critical *t* value is employed in evaluating the computed *t* value.

Before describing one of procedures that can be employed when the homogeneity of variance assumption is violated, it should be pointed out that the existence of heterogeneity of variance in a set of data may in itself be noteworthy. It is conceivable that although the analysis of the data for an experiment may indicate that there is no difference between the group means, one cannot rule out the possibility that there may be a significant difference between the variances of the two groups. This latter finding may be of practical importance in clarifying the relationship between the variables under study. This general issue is addressed in Section VIII of the **single-sample runs test (Test 10)** within the framework of the discussion of Example 10.6. In the latter discussion, an experiment is described in which subjects in an experimental group who receive an antidepressant either improve dramatically or regress while on the drug. In contrast, the scores of a placebo/control group exhibit little variability, and fall in between the two extreme sets of scores in the group that receives the antidepressant. Analysis of such a study with the ***t* test for two independent samples** will in all likelihood not yield a significant result, since the two groups will probably have approximately the same mean depression score. The fact that the group receiving the drug exhibits greater variability than the group receiving the placebo indicates that the effect of the drug is not consistent for all people who are depressed. Such an effect can be identified through use of a test such as the F_{\max} test, which contrasts the variability of two groups.

Two statisticians (Behrens and Fisher) developed a sampling distribution for the *t* statistic when the homogeneity of variance assumption is violated. The latter sampling distribution is referred to as the *t'* distribution. Since tables of critical values developed by Behrens and Fisher can only be employed for a limited number of sample sizes, Cochran and Cox (1957) developed a methodology that allows one to compute critical values of *t'* for all values of n_1 and n_2 . Equation 11.9 summarizes the computation of *t'*.

$$t' = \frac{t_1 \left[\frac{\hat{s}_1^2}{n_1} \right] + t_2 \left[\frac{\hat{s}_2^2}{n_2} \right]}{\frac{\hat{s}_1^2}{n_1} + \frac{\hat{s}_2^2}{n_2}} \quad (\text{Equation 11.9})$$

Where: t_1 = The tabled critical t value at the prespecified level of significance for $df = n_1 - 1$
 t_2 = The tabled critical t value at the prespecified level of significance for $df = n_2 - 2$

Equation 11.9 will be employed with the data for Example 11.1. For purposes of illustration, it will be assumed that the homogeneity of variance assumption has been violated, and that the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is evaluated, with $\alpha = .05$. Since $n_1 = n_2 = n = 5$, $df_1 = df_2 = n - 1 = 4$. Employing [Table A2](#), we determine that for $\alpha = .05$ and $df = 4$, the tabled critical two-tailed .05 value is $t_{.05} = 2.78$. Thus, the values $t_1 = 2.78$ and $t_2 = 2.78$ are substituted in Equation 11.9, along with the values of the estimated population variances and the sample sizes.¹⁴

$$t' = \frac{2.78 \left[\frac{21.7}{5} \right] + 2.78 \left[\frac{10.7}{5} \right]}{\frac{21.7}{5} + \frac{10.7}{5}} = 2.78$$

Note that the computed value $t' = 2.78$ is larger than the tabled critical two-tailed .05 value $t_{.05} = 2.31$, which is employed if the homogeneity of variance adjustment is not violated. Since the value of t' will always be larger than the tabled critical t value at the prespecified level of significance for $df = n_1 + n_2 - 2$ (except for the instance noted in Endnote 14), use of the t' statistic will result in a more conservative test. In our hypothetical example, use of the t' statistic is designed to insure that the Type I error rate will conform to the prespecified value $\alpha = .05$. If there is heterogeneity of variance and the homogeneity of variance adjustment is not employed, the actual alpha level will be greater than $\alpha = .05$. Since in our example the computed value $t' = 2.78$ is larger than the computed absolute value $t = 1.96$ obtained for the t test, the null hypothesis cannot be rejected. The methodology described in this section for dealing with heterogeneity of variance provides for a slightly more conservative **t test for two independent samples** than do alternative strategies developed by Satterthwaite (1946) and Welch (1947) (which are described in Howell (1992) and Winer *et al.* (1991)). Another strategy for dealing with heterogeneity of variance is to employ, in lieu of the **t test**, a nonparametric test which does not assume homogeneity of variance.

3. Computation of the power of the t test for two independent samples and the application of Test 11b: Cohen's d index In this section two methods for computing power, which are extensions of the methods presented for computing the power of the **single-sample t test**, will be described. Prior to reading this section the reader should review the discussion of power in Section VI of the latter test.

Method 1 for computing the power of the t test for two independent samples The first procedure to be described is a graphical method which reveals the logic underlying the power computations for the **t test for two independent samples**. In the discussion to follow, it will be

assumed that the null hypothesis is identical to that employed for Example 11.1 (i.e., $H_0: \mu_1 - \mu_2 = 0$, which, as previously noted, is another way of writing $H_0: \mu_1 = \mu_2$). It will also be assumed that the researcher wants to evaluate the power of the *t* test for two independent samples in reference to the following alternative hypothesis: $H_1: |\mu_1 - \mu_2| \geq 5$ (which is the difference obtained between the sample means in Example 11.1). In other words, it is predicted that the absolute value of the difference between the two means is equal to or greater than 5. The latter alternative hypothesis is employed in lieu of $H_0: \mu_1 - \mu_2 \neq 0$ (which can also be written as $H_1: \mu_1 \neq \mu_2$), since in order to compute the power of the test, a specific value must be stated for the difference between the population means. Note that, as stated, the alternative hypothesis stipulates a nondirectional analysis, since it does not specify which of the two means will be the larger value. It will be assumed that $\alpha = .05$ is employed in the analysis.

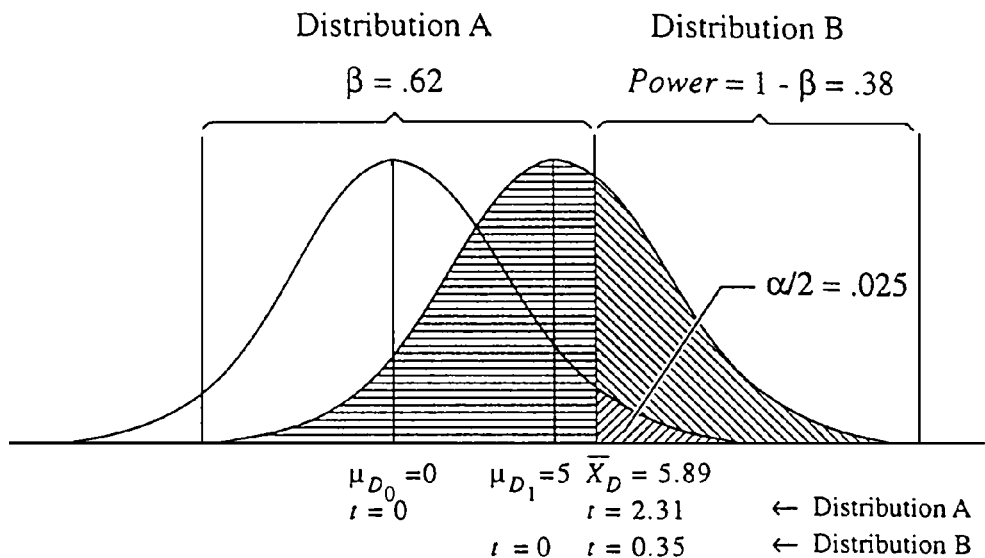


Figure 11.1 Visual Representation of Power for Example 11.1

Figure 11.1, which provides a visual summary of the power analysis, is comprised of two overlapping sampling distributions of difference scores. The distribution on the left, which will be designated as Distribution A, is a sampling distribution of difference scores that has a mean value of zero (i.e., $\mu_D = \mu_{\bar{X}_1} - \bar{X}_2 = 0$). This latter value will be represented by $\mu_{D_0} = 0$ in Figure 11.1. Distribution A represents the sampling distribution that describes the distribution of difference scores if the null hypothesis is true. The distribution on the right, which will be designated as Distribution B, is a sampling distribution of difference scores that has a mean value of 5 (i.e., $\mu_D = \mu_{\bar{X}_1} - \bar{X}_2 = 5$). This latter value will be represented by $\mu_{D_1} = 5$ in Figure 11.1. Distribution B represents the sampling distribution that describes the distribution of difference scores if the alternative hypothesis is true. It will be assumed that each of the sampling distributions has a standard deviation that is equal to the value computed for the standard error of the difference in Example 11.1 (i.e., $s_{\bar{X}_1 - \bar{X}_2} = 2.55$), since the latter value provides the best estimate of the standard deviation of the difference scores for the underlying populations.

In Figure 11.1, area (///) delineates the proportion of Distribution A that corresponds to the value $\alpha/2$, which equals .025. This is the case, since $\alpha = .05$ and a two-tailed analysis is conducted. Area (≡) delineates the proportion of Distribution B that corresponds to the

probability of committing a Type II error (β). Area (\\) delineates the proportion of Distribution B that represents the power of the test (i.e., $1 - \beta$).

The procedure for computing the proportions documented in Figure 11.1 will now be described. The first step in computing the power of the test requires one to determine how large a difference there must be between the sample means in order to reject the null hypothesis. In order to do this, we algebraically transpose the terms in Equation 11.1, using $s_{\bar{X}_1 - \bar{X}_2}$ to summarize the denominator of the equation, and $t_{.05}$ (the tabled critical two-tailed .05 t value) to represent t . Thus: $\bar{X}_1 - \bar{X}_2 = (t_{.05})(s_{\bar{X}_1 - \bar{X}_2})$. By substituting the values $t_{.05} = 2.31$ and $s_{\bar{X}_1 - \bar{X}_2} = 2.55$ in the latter equation, we determine that the minimum required difference is $\bar{X}_1 - \bar{X}_2 = (2.31)(2.55) = 5.89$. Thus, any difference between the two population means that is equal to or greater than 5.89 will allow the researcher to reject the null hypothesis at the .05 level.

The next step in the analysis requires one to compute the area in Distribution B that falls between the mean difference $\mu_{D_1} = 5$ (i.e., the mean of Distribution B) and a mean difference equal to 5.89 (represented by the notation $\bar{X}_D = 5.89$ in Figure 11.1). This is accomplished by employing Equation 11.1. In using the latter equation, the value of \bar{X}_1 is represented by 5.89 and the value of \bar{X}_2 by $\mu_{D_1} = 5$.

$$t = \frac{\bar{X}_1 - \bar{X}_2}{s_{\bar{X}_1 - \bar{X}_2}} = \frac{5.89 - 5}{2.55} = .35$$

By interpolating the values listed in Table A2 for $df = 8$, we determine that the proportion of Distribution B that lies to the right of a t score of .35 (which corresponds to a mean difference of 5.89) is approximately .38. The latter area corresponds to area (\\) in Distribution B. Note that the left boundary of area (\\) is also the boundary delineating the extreme 2.5% of Distribution A (i.e., $\alpha/2 = .025$, which is the rejection zone for the null hypothesis). Since area (\\) in Distribution B overlaps the rejection zone in Distribution A, area (\\) represents the power of the test — i.e., it represents the likelihood of rejecting the null hypothesis if the alternative hypothesis is true. The likelihood of committing a Type II error (β) is represented by area (=), which comprises the remainder of Distribution B. The proportion of Distribution B that constitutes this latter area is determined by subtracting the value .38 from 1. Thus: $\beta = 1 - .38 = .62$.

Based on the results of the power analysis, we can state that if the alternative hypothesis $H_1: |\mu_1 - \mu_2| \geq 5$ is true, the likelihood that the null hypothesis will be rejected is .38, and at the same time there is a .62 likelihood that it will be retained. If the researcher considers the computed value for power too low (which in actuality should be determined prior to conducting a study), she can increase the power of the test by employing a larger sample size.

Method 2 for computing the power of the t test for two independent samples employing Test 11b: Cohen's d index Method 2, the quick computational method described for computing the power of the **single sample t test**, can be extended to the **t test for two independent samples**. In using the latter method, the researcher must stipulate an **effect size (d)**, which in the case of the **t test for two independent samples** is computed with Equation 11.10. The effect size index computed with Equation 11.10 was developed by Cohen (1977, 1988), and is known as **Cohen's d index**. Further discussion of **Cohen's d index** can be found in the next section dealing with magnitude of treatment effect, as well as in Section IX (the **Appendix**) of the **Pearson product-moment correlation coefficient (Test 28)** under the discussion of **meta-analysis and related topics**.

$$d = \frac{|\mu_1 - \mu_2|}{\sigma} \quad (\text{Equation 11.10})$$

The numerator of Equation 11.10 represents the hypothesized difference between the two population means. As is the case with the graphical method described previously, when a power analysis is conducted after the mean of each sample has been obtained, the difference between the two sample means (i.e., $\bar{X}_1 - \bar{X}_2$) is employed as an estimate of the value of $|\mu_1 - \mu_2|$. It is assumed that the value of the standard deviation for the variable being measured is the same in each of the populations, and the latter value is employed to represent σ in the denominator of Equation 11.10 (i.e., $\sigma = \sigma_1 = \sigma_2$). In instances where the standard deviations of the two populations are not known or cannot be estimated, the latter value can be estimated from the sample data. Because of the fact that \tilde{s}_1 will usually not equal \tilde{s}_2 , a pooled estimated population standard deviation (\tilde{s}_p) can be computed with Equation 11.11 (which is the square root of \tilde{s}_p^2 discussed in Section IV with reference to Equation 11.3).

$$\tilde{s}_p = \sqrt{\frac{(n_1 - 1)\tilde{s}_1^2 + (n_2 - 1)\tilde{s}_2^2}{n_1 + n_2 - 2}} \quad (\text{Equation 11.11})$$

Since the effect size computed with Equation 11.10 is based on population parameters, it is necessary to convert the value of d into a measure that takes into account the size of the samples (which is a relevant variable in determining the power of the test). This measure, as noted in the discussion of the **single-sample t test**, is referred to as the **noncentrality parameter**. Equation 11.12 is employed to compute the **noncentrality parameter** (δ) for the **t test for two independent samples**. When the sample sizes are equal, the value of n in Equation 11.12 will be $n = n_1 = n_2$. When the sample sizes are unequal, the value of n will be represented by the **harmonic mean** of the sample sizes, which is described later in this section.

$$\delta = d \sqrt{\frac{n}{2}} \quad (\text{Equation 11.12})$$

The power of the **t test for two independent samples** will now be computed using the data for Example 11.1. For purposes of illustration, it will be assumed that the minimum difference between the population means the researcher is trying to detect is the observed 5 point difference between the two sample means — i.e., $|\bar{X}_1 - \bar{X}_2| = |2.8 - 7.8| = 5 = |\mu_1 - \mu_2|$. The value of σ employed in Equation 11.10 is estimated by computing a pooled value for the standard deviation using Equation 11.11. Substituting the relevant values from Example 11.1 in Equation 11.11, the value $\tilde{s}_p = 4.02$ is computed.

$$\tilde{s}_p = \sqrt{\frac{(5 - 1)(21.7) + (5 - 1)(10.7)}{5 + 5 - 2}} = 4.02$$

Substituting $|\mu_1 - \mu_2| = 5$ and $\sigma = 4.02$ in Equation 11.10, the value $d = 1.24$ is computed.

$$d = \frac{5}{4.02} = 1.24$$

Cohen (1977; 1988, pp. 24–27) has proposed the following (admittedly arbitrary) d values

as criteria for identifying the magnitude of an effect size: a) A **small effect size** is one that is greater than .2 but not more than .5 standard deviation units; b) A **medium effect size** is one that is greater than .5 but not more than .8 standard deviation units; and c) A **large effect size** is greater than .8 standard deviation units. Employing Cohen's (1977, 1988) guidelines, the value $d = 1.24$ (which represents 1.24 standard deviation units) is categorized as a large effect size.

Along with the value $n = 5$ (since $n_1 = n_2 = n = 5$), the value $d = 1.24$ is substituted in Equation 11.12, resulting in the value $\delta = 1.96$.

$$\delta = 1.24 \sqrt{\frac{5}{2}} = 1.96$$

The value $\delta = 1.96$ is evaluated with **Table A3 (Power Curves for Student's t Distribution)** in the **Appendix**. We will assume that for the example under discussion a two-tailed test is conducted with $\alpha = .05$, and thus **Table A3-C** is the appropriate set of power curves to employ for the analysis. Since there is no curve for $df = 8$, the power of the test will be based on a curve that falls in between the $df = 6$ and $df = 12$ power curves. Through interpolation, the power of the **t test for two independent samples** is determined to be approximately .38 (which is the same value that is obtained with the graphical method). Thus, by employing 5 subjects in each group the researcher has a probability of .38 of rejecting the null hypothesis if the true difference between the population means is equal to or greater than 1.24 standard deviation units (which in Example 11.1 is equivalent to a 5 point difference between the means). It should be noted that in employing Equation 11.12, the smaller the value of n the smaller the computed value of δ , and consequently the lower the power of the test.

It was noted earlier in the discussion that when the sample sizes are unequal, the value of n in Equation 11.12 is represented by the **harmonic mean** of the sample sizes (which will be represented by the notation \bar{n}_h). The harmonic mean is computed with Equation 11.13.

$$\bar{n}_h = \frac{k}{\sum_{j=1}^k \left[\frac{1}{n_j} \right]} \quad \text{(Equation 11.13)}$$

Where: k = The number of groups

n_j = The number of subjects in the j^{th} group

The use of Equation 11.13 will be illustrated for a case in which there is a total of 10 subjects, but there is an unequal number of subjects in each group. Thus, let us assume that $n_1 = 7$ and $n_2 = 3$. The harmonic mean can be computed as follows: $\bar{n}_h = 2/[(1/7) + (1/3)] = 4.20$. The reader should take note of the fact that the value $\bar{n}_h = 4.20$ computed for the harmonic mean is lower than the average number of subjects per group (\bar{n}), which is computed to be $\bar{n} = (7 + 3)/2 = 5$. In point of fact, \bar{n}_h will always be lower than \bar{n} unless $n_1 = n_2$, in which case $\bar{n}_h = \bar{n}$. Since, when $n_1 \neq n_2$, \bar{n}_h will always be less than \bar{n} , it follows that when $n_1 \neq n_2$, the value computed for the power of the test when the harmonic mean is employed in Equation 11.12 will be less than the value that is computed for the power of the test if \bar{n} is employed to represent the value of n . This translates into the fact that for a specific total sample size (i.e., $n_1 + n_2$), the power of the **t test for two independent samples** will be maximized when $n_1 = n_2$.

As is the case with power computations for the **single-sample t test**, as long as a researcher knows or is able to estimate (from the sample data) the population standard deviation, by

employing trial and error she can substitute various values of n in Equation 11.12, until the computed value of δ corresponds to the desired power value for the **t test for two independent samples** for a given effect size. This process can be facilitated by employing tables developed by Cohen (1977, 1988), which allow one to determine the minimum sample size necessary in order to achieve a specific level of power in reference to a given effect size.

4. Measure of magnitude of treatment effect for the t test for two independent samples: Omega squared (Test 11c) At the conclusion of an experiment a researcher may want to determine the proportion of the variability on the dependent variable that is associated with the experimental treatments (i.e., the independent variable). This latter value is commonly referred to as the **treatment effect**.¹⁵ Unfortunately, the t value computed for the **t test for two independent samples** does not in itself provide information regarding the magnitude of a treatment effect. The reason for this is that the absolute value of t is not only a function of the treatment effect, but is also a function of the size of the sample employed in an experiment. Since the power of a statistical test is directly related to sample size, the larger the sample size, the more likely a significant t value will be obtained if there is any difference between the means of the underlying populations. Regardless of how small a treatment effect is present, the magnitude of the absolute value of t will increase as the size of the sample employed to detect that effect increases. Thus, a t value that is significant at any level (be it .05, .01, .001, etc.) can result from the presence of a large, medium, or small treatment effect.

Before describing measures of treatment effect for the **t test for two independent samples**, the distinction between **statistical significance** and **practical significance** (which is discussed briefly in the **Introduction**) will be clarified. Whereas **statistical significance** only indicates that a difference between the two group means has been detected and that the difference is unlikely to be the result of chance, **practical significance** refers to the practical implications of the obtained difference. As just noted, by employing a large sample size, a researcher will be able to detect differences between means that are extremely small. Although in some instances a small treatment effect can be of practical significance, more often than not a minimal difference will be of little or no practical value (other than perhaps allowing a researcher to get a study published, since significant results are more likely to be published than nonsignificant results). On the other hand, the larger the magnitude of treatment effect computed for an experiment, the more likely the results have practical implications. To go even further, when a researcher employs a small sample size, it is possible to have a moderate or large treatment effect present, yet not obtain a statistically significant result. Obviously, in such an instance (which represents an example of a Type II error) the computed t value is misleading with respect to the truth regarding the relationship between the variables under study.

A number of indices for measuring magnitude of treatment effect have been developed. Unlike the computed t value, measures of magnitude of treatment effect provide an index of the degree of relationship between the independent and dependent variables that is independent of sample size.¹⁶ A major problem with measures of treatment effect is that for most experimental designs two or more such measures are available which are not equivalent to one another, and researchers are often not in agreement with respect to which measure is appropriate to employ. In the case of the **t test for two independent samples**, the most commonly employed measure of treatment effect is **omega squared**. The statistic that is computed from the sample data to estimate the value of **omega squared** is represented by the notation $\hat{\omega}^2$ (ω is the lower case Greek letter **omega**). This latter value provides an estimate of the underlying population parameter ω^2 , which represents the proportion of variability on the dependent variable that is associated with the independent variable in the underlying population. The value of $\hat{\omega}^2$ is computed with Equation 11.14.

$$\tilde{\omega}^2 = \frac{t^2 - 1}{t^2 + n_1 + n_2 - 1} \quad (\text{Equation 11.14})$$

Although the value of $\tilde{\omega}^2$ will generally fall in the range between 0 and 1, when $|t| < 1$, $\tilde{\omega}^2$ will be a negative number. The closer $\tilde{\omega}^2$ is to 1, the stronger the association between the independent and dependent variables, whereas the closer $\tilde{\omega}^2$ is to 0, the weaker the association between the two variables. A $\tilde{\omega}^2$ value equal to or less than 0 indicates that there is no association between the variables.¹⁷

Employing Equation 11.14 with the data for Example 11.1, the value $\tilde{\omega}^2 = .22$ is computed.

$$\tilde{\omega}^2 = \frac{(-1.96)^2 - 1}{(-1.96)^2 + 5 + 5 - 1} = .22$$

The value $\tilde{\omega}^2 = .22$ indicates that 22% (or a proportion equal to .22) of the variability on the dependent variable (the depression ratings of the subjects) is associated with variability on the levels of the independent variable (the drug versus placebo conditions). To say it another way, 22% of the variability on the depression scores can be accounted for on the basis of which group a subject is a member.

Cohen (1977; 1988, pp. 285–288) has suggested the following (admittedly arbitrary) values, which are employed in psychology and a number of other disciplines, as guidelines for interpreting $\tilde{\omega}^2$: a) A **small effect size** is one that is greater than .0099 but not more than .0588; b) A **medium effect size** is one that is greater than .0588 but not more than .1379; and c) A **large effect size** is greater than .1379.¹⁸ In the case of Example 11.1, if one employs Cohen's (1977, 1988) guidelines, the obtained value $\tilde{\omega}^2 = .22$ indicates the presence of a large treatment effect.

Keppel (1991) and Keppel *et al.* (1992) note that in the experimental literature in the discipline of psychology it is unusual for a $\tilde{\omega}^2$ value to exceed .25 — indeed, one review of the psychological literature yielded an average $\tilde{\omega}^2$ value of .06. The inability of researchers to control experimental error with great precision is the most commonly cited reason for the low value obtained for $\tilde{\omega}^2$ in most studies.

Eta squared (η^2) is an alternative but less commonly used measure of association that can also be employed to evaluate the magnitude of a treatment effect for a ***t* test for two independent samples**. The **eta squared (Test 21h)** statistic is described in Section VI of the **single-factor between-subjects analysis of variance**. Most sources note that **eta squared** results in a more biased estimate of the degree of association in the underlying population than does **omega squared**. **Eta squared** is also discussed under the **Pearson product-moment correlation coefficient** with reference to the **point-biserial correlation coefficient (Test 28h)**. In the latter discussion, it is demonstrated that **eta squared** and the **point-biserial correlation coefficient** are equivalent measures when they are used to evaluate magnitude of treatment effect for a design involving two independent samples. In the discussion of the **single-factor between-subjects analysis of variance**, it is noted that if η^2 and $\tilde{\omega}^2$ are computed for the same set of data, they yield different values. The issue of the lack of agreement among different magnitude of treatment effect measures is considered in more detail in Section VI of the **single-factor between-subjects analysis of variance**.

In closing the discussion of magnitude of treatment effect, it should be noted that at the present time many sources recommend that in reporting the results of an experimental analysis with an inferential statistical test (such as the ***t* test for two independent samples**), in addition to reporting the computed test statistic (e.g., a *t* value), the researcher should also present a measure of the magnitude of treatment effect (e.g., $\tilde{\omega}^2$), since, by including the latter value, one is providing additional information that can further clarify the nature of the relationship between

the variables under study. A general discussion of the latter issue, as well as a additional discussion of measures of treatment effect can be found in Section IX (the **Addendum**) of the **Pearson product-moment correlation coefficient** under the discussion of **meta-analysis and related topics**.

5. Computation of a confidence interval for the t test for two independent samples Prior to reading this section the reader should review the discussion on the computation of confidence intervals in Section VI of the **single-sample t test**. When interval/ratio data are available for two independent samples, a confidence interval can be computed that identifies a range of values within which one can be confident to a specified degree that the true difference lies between the two population means. Equation 11.15 is the general equation for computing the confidence interval for the difference between the means of two independent populations.

$$CI_{(1 - \alpha)} = (\bar{X}_1 - \bar{X}_2) \pm (t_{\alpha/2})(s_{\bar{X}_1 - \bar{X}_2}) \quad \text{(Equation 11.15)}$$

Where: $t_{\alpha/2}$ represents the tabled critical two-tailed value in the t distribution, for $df = n_1 + n_2 - 2$, below which a proportion (percentage) equal to $[1 - (\alpha/2)]$ of the cases falls. If the proportion (percentage) of the distribution that falls within the confidence interval is subtracted from 1 (100%), it will equal the value of α

Employing Equation 11.15, the 95% interval for Example 11.1 is computed below. In employing Equation 11.15, $(\bar{X}_1 - \bar{X}_2)$ represents the obtained difference between the group means (which is the numerator of the equation used to compute the value of t), $t_{.05}$ represents the tabled critical two-tailed .05 value for $df = n_1 + n_2 - 2$, and $s_{\bar{X}_1 - \bar{X}_2}$ represents the standard error of the difference (which is the denominator of the equation used to compute the value of t).

$$CI_{.95} = (\bar{X}_1 - \bar{X}_2) \pm (t_{.05})(s_{\bar{X}_1 - \bar{X}_2}) = -5 \pm (2.31)(2.55) = -5 \pm 5.89$$

$$-10.89 \leq (\mu_1 - \mu_2) \leq .89$$

This result indicates that the researcher can be 95% confident (or the probability is .95) that the true difference between the population means falls within the range -10.89 and $.89$. Specifically, it indicates that one can be 95% confident (or the probability is .95) that the mean of the population Group 2 represents is no more than 10.89 points higher than the mean of population that Group 1 represents, and that the mean of population that Group 1 represents is no more than .89 points higher than the mean of population that Group 2 represents.¹⁹

Note that in using the above notation, when a confidence interval range involves both a negative and positive limit (as is the case in the above example), it indicates that it is possible for either of the two population means to be the larger value. If, on the other hand, both limits identified by the confidence interval are positive values, the mean of Population 1 will always be greater than the mean of Population 2. If both limits identified by the confidence interval are negative values, the mean of Population 2 will always be greater than the mean of Population 1.

The 99% confidence interval for Example 11.1 will also be computed to illustrate that the range of values that define a 99% confidence interval is always larger than the range which defines a 95% confidence interval.

$$CI_{.99} = (\bar{X}_1 - \bar{X}_2) \pm (t_{.01})(s_{\bar{X}_1 - \bar{X}_2}) = -5 \pm (3.36)(2.55) = -5 \pm 8.57$$

$$-13.57 \leq (\mu_1 - \mu_2) \leq 3.57$$

Thus, the researcher can be 99% confident (or the probability is .99) that the true difference between the population means falls within the range -13.57 and 3.57 . Specifically, it indicates that one can be 99% confident (or the probability is .99) that the mean of the population Group 2 represents is no more than 13.57 points higher than the mean of population that Group 1 represents, and that the mean of population that Group 1 represents is no more than 3.57 points higher than the mean of population that Group 2 represents. In closing the discussion of confidence intervals, it is worth noting that the broad range of values that define the above computed confidence intervals will not allow a researcher to estimate with great precision the actual difference between the means of the underlying populations. Additionally, the reader should take note of the fact that the reliability of Equation 11.15 will be compromised if one or more of the assumptions of the ***t* test for two independent samples** are saliently violated.

6. Test 11d: The *z* test for two independent samples There are occasions (albeit infrequent) when a researcher wants to compare the means of two independent samples, and happens to know the variances of the two underlying populations. In such a case, the ***z* test for two independent samples** should be employed to evaluate the data instead of the ***t* test for two independent samples**. As is the case with the latter test, the ***z* test for two independent samples** assumes that the two samples are randomly selected from populations that have normal distributions. The effect of violation of the normality assumption on the test statistic decreases as the size of the samples employed in an experiment increase. The homogeneity of variance assumption noted for the ***t* test for two independent samples** is not an assumption of the ***z* test for two independent samples**.

The null and alternative hypotheses employed for the ***z* test for two independent samples** are identical to those employed for the ***t* test for two independent samples**. Equation 11.16 is employed to compute the test statistic for the ***z* test for two independent samples**.

$$z = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}} \quad \text{(Equation 11.16)}$$

The only differences between Equation 11.16 and Equation 11.1 (the equation for the ***t* test for two independent samples**) are: a) In the denominator of Equation 11.16 the population variances σ_1^2 and σ_2^2 are employed instead of the estimated population variances \hat{s}_1^2 and \hat{s}_2^2 (which are employed in Equation 11.1); and b) Equation 11.16 computes a *z* score which is evaluated with the normal distribution, while Equation 11.1 derives a *t* score which is evaluated with the *t* distribution. Unlike Equation 11.1, Equation 11.16 can be used with both equal and unequal sample sizes.²⁰

If it is assumed that the two population variances are known in Example 11.1, and that $\sigma_1^2 = 21.7$ and $\sigma_2^2 = 10.7$, Equation 11.16 can be employed to evaluate the data. Note that the obtained value $z = -1.96$ is identical to the value that is computed for *t* when Equation 11.1 is employed.

$$z = \frac{2.8 - 7.8}{\sqrt{\frac{21.7}{5} + \frac{10.7}{5}}} = -1.96$$

The obtained value $z = -1.96$ is evaluated with **Table A1 (Table of the Normal**

Distribution) in the **Appendix**. In **Table A1** the tabled critical two-tailed .05 and .01 values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed .05 and .01 values are $z_{.05} = 1.65$ and $z_{.01} = 2.33$. Since the computed absolute value $z = 1.96$ is equal to the tabled critical two-tailed value $z_{.05} = 1.96$, the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is supported at the .05 level. Since the computed value $z = -1.96$ is a negative number and the absolute value of z is greater than the tabled critical one-tailed .05 value $z_{.05} = 1.65$, the directional alternative hypothesis $H_1: \mu_1 < \mu_2$ is also supported at the .05 level.

When the same set of data is evaluated with the ***t* test for two independent samples**, although the directional alternative hypothesis $H_1: \mu_1 < \mu_2$ is supported at the .05 level, the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is not supported. This latter fact illustrates that if the ***z* test for two independent samples** and the ***t* test for two independent samples** are employed to evaluate the same set of data (except when the value of $n_1 + n_2 - 2$ is extremely large), the latter test will provide a more conservative test of the null hypothesis (i.e., make it more difficult to reject H_0). This is the case, since the tabled critical values listed for the ***z* test for two independent samples** will always correspond to the tabled critical values listed in **Table A2** for $df = \infty$ (which are the lowest tabled critical values listed for the *t* distribution).

The final part of the discussion of the ***z* test for two independent samples** will describe a special case of the test in which it is employed to evaluate the difference between the average performance of two samples for whom scores have been obtained on a binomially distributed variable. Example 11.3, which is used to illustrate this application of the test, is an extension of Example 9.6 (discussed under the ***z* test for a population proportion (Test 9a)**) to a design involving two independent samples.

Example 11.3 *An experiment is conducted in which the performance of two groups is contrasted on a test of extrasensory perception. The two groups are comprised of five subjects who believe in extrasensory perception (Group 1) and five subjects who do not believe in it (Group 2). The researcher employs as test stimuli a list of 200 binary digits (specifically, the values 0 and 1) which have been randomly generated by a computer. During the experiment an associate of the researcher concentrates on each of the digits in the order it appears on the list. While the associate does this, each of the ten subjects, all of whom are in separate rooms, attempts to guess the value of the number for each of 200 trials. The number of correct guesses for the two groups of subjects follow: **Group 1:** 105, 120, 130, 115, 110; **Group 2:** 104, 99, 90, 100, 107. Is there a difference in the performance of the two groups?*

The null and alternative hypotheses evaluated in Example 11.3 are identical to those evaluated in Example 11.1. Example 11.3 is evaluated with Equation 11.17, which is the form Equation 11.16 assumes when $\sigma_1^2 = \sigma_2^2$. Note that in Equation 11.17, m_j is employed to represent the number of subjects in the j^{th} group, since the notation n is employed with a binomially distributed variable to designate the number of trials each subject is tested. Thus, $m_1 = m_2 = 5$.

$$z = \frac{\bar{X}_1 - \bar{X}_2}{\sigma \sqrt{\frac{1}{m_1} + \frac{1}{m_2}}} \quad (\text{Equation 11.17})$$

In employing Equation 11.17, we first compute the average score of each of the groups: $\bar{X}_1 = 580/5 = 116$ and $\bar{X}_2 = 500/5 = 100$. Since scores on the binary guessing task described in Example 11.3 are assumed to be binomially distributed, as is the case in Example 9.6, the

following is true: $n = 200$, $\pi_1 = .5$, and $\pi_2 = .5$. The computed value for the population standard deviation for the binomially distributed variable is $\sigma = \sqrt{n\pi_1\pi_2} = \sqrt{(200)(.5)(.5)} = 7.07$. (The computation of the latter values is discussed in Section I of the **binomial sign test for a single sample (Test 9)**.) When the appropriate values are substituted in Equation 11.17, the value $z = 3.58$ is computed.

$$z = \frac{116 - 100}{7.07 \sqrt{\frac{1}{5} + \frac{1}{5}}} = 3.58$$

Since the computed absolute value $z = 3.58$ is greater than the tabled critical two-tailed values $z_{.05} = 1.96$ and $z_{.01} = 2.58$, the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is supported at both the .05 and .01 levels. Since the computed value $z = 3.58$ is a positive number that is greater than the tabled critical one-tailed values $z_{.05} = 1.65$ and $z_{.01} = 2.33$, the directional alternative hypothesis $H_1: \mu_1 > \mu_2$ is supported at both the .05 and .01 levels. Thus, it can be concluded that the average score of Group 1 is significantly larger than the average score of Group 2.

After employing Equation 11.17 to evaluate an experiment such as the one described in Example 11.3, a researcher may want to determine whether either of the group averages is above or below the expected mean value (which, in Example 11.3, is $\mu = n\pi_1 = (200)(.5) = 100$). Equation 9.10 is employed to evaluate the performance of a single group. The null hypothesis that is employed for evaluating a single group is $H_0: \pi_1 = .5$ (which, for Example 11.3, is commensurate with $H_0: \mu_j = 100$), and the nondirectional alternative hypothesis is $H_1: \pi_1 \neq .5$ (which, for Example 11.3, is commensurate with $H_1: \mu_j \neq 100$). Since it is obvious from inspection of the data that the performance of Group 2 is at chance expectancy, the performance of Group 1, which is above chance, will be evaluated with Equation 9.10.

$$z = \frac{\bar{X} - \mu}{\frac{\sigma}{\sqrt{m}}} = \frac{116 - 100}{\frac{7.07}{\sqrt{5}}} = 5.06$$

Since the computed value $z = 5.06$ is greater than the tabled critical two-tailed values $z_{.05} = 1.96$ and $z_{.01} = 2.58$, the nondirectional alternative hypothesis $H_1: \pi_1 \neq .5$ is supported at both the .05 and .01 levels. Since the computed value $z = 5.06$ is a positive number that is greater than the tabled critical one-tailed values $z_{.05} = 1.65$ and $z_{.01} = 2.33$, the directional alternative hypothesis $H_1: \pi_1 > .5$ is also supported at both the .05 and .01 levels. Thus, it can be concluded that the average performance of Group 1 is significantly above chance.

VII. Additional Discussion of the *t* Test for Two Independent Samples

1. Unequal sample sizes In Section IV it is noted that if Equation 11.1/11.2 (which can only be used when $n_1 = n_2$) is applied to data where $n_1 \neq n_2$, the absolute value of *t* will be larger than the value computed with Equation 11.3. To illustrate this point, Equations 11.1 and 11.3 will be applied to a modified form of Example 11.1. Specifically, one of the scores in Group 2 will be eliminated from the data. If the score of Subject 1 (i.e., 11) is eliminated, the four scores that remain are: 11, 5, 8, 4. Employing the latter values, $n_2 = 4$, $\sum X_2 = 28$, $\sum X_2^2 = 226$, $\bar{X}_2 = 7$, $s_2^2 = [226 - (28)^2/4]/(4 - 1) = 10$. For Group 1 the values $n_1 = 5$, $\bar{X}_1 = 2.8$, and $s_1^2 = 21.7$

remain unchanged. The relevant values are substituted in Equation 11.1.

$$t = \frac{2.8 - 7}{\sqrt{\frac{21.7}{5} + \frac{10}{4}}} = -1.61$$

The same information is now substituted in Equation 11.3.

$$t = \frac{2.8 - 7}{\sqrt{\left[\frac{(5 - 1)(21.7) + (4 - 1)(10)}{5 + 4 - 2} \right] \left[\frac{1}{5} + \frac{1}{4} \right]}} = -1.53$$

Note that the absolute value $t = 1.61$ computed with Equation 11.1 is larger than the absolute value $t = 1.53$ computed with Equation 11.3, and thus Equation 11.3 provides a more conservative test of the null hypothesis. It so happens that in this instance neither of the computed t values allows the null hypothesis to be rejected since, for $df = 5 + 4 - 2 = 7$, both absolute values are below the tabled critical two-tailed values $t_{.05} = 2.37$ and $t_{.01} = 3.50$, and the tabled critical one-tailed values $t_{.05} = 1.90$ and $t_{.01} = 3.00$.

2. Robustness of the t test for two independent samples²¹ Some statisticians believe that if one or more of the assumptions of a parametric test (such as the **t test for two independent samples**) are saliently violated, the test results will be unreliable, and because of this under such conditions it is more prudent to employ the analogous nonparametric test, which will generally have fewer or less rigorous assumptions than its parametric analog. In the case of the **t test for two independent samples** the most commonly employed analogous nonparametric tests are the **Mann–Whitney U test (Test 12)** and the **chi-square test for $r \times c$ tables (Test 16)**. Use of the **Mann–Whitney U test** (which is most likely to be recommended when the normality assumption of the **t test for two independent samples** is saliently violated) requires that the original interval/ratio scores be transformed into a rank-order format. By virtue of rank-ordering the data, information is sacrificed (since rank-orderings do not provide information regarding the magnitude of the differences between adjacent ranks). Given the fact that the **Mann–Whitney U test** employs less information, many researchers if given the choice will still elect to employ the **t test for two independent samples**, even if there is reason to believe that the normality assumption of the latter test is violated. Under such conditions, however, most researchers would probably conduct a more conservative t test in order to avoid inflating the likelihood of committing a Type I error (i.e., one might employ the tabled critical $t_{.01}$ value to represent the $t_{.05}$ value instead of the actual value listed for $t_{.05}$). In the unlikely event that a researcher elects to employ the **chi-square test for $r \times c$ tables** in place of the **t test for two independent samples**, he must convert the original interval/ratio data into a categorical format. This latter type of a transformation will result in an even greater loss of information than is the case with the **Mann–Whitney U test**.

The justification for using a parametric test in lieu of its nonparametric analog, even when one or more of the assumptions of the former test are violated, is that the results of numerous empirical sampling studies have demonstrated that under most conditions a parametric test like the **t test for two independent samples** is reasonably **robust**. A **robust** test is one that still provides reliable information about the underlying sampling distribution, in spite of the fact that one or more of the test's assumptions have been violated. In addition, researchers who are reluctant to employ nonparametric tests argue that parametric tests, such as the **t test for two independent**

samples, are more powerful than their nonparametric analogs. Proponents of nonparametric tests counter with the argument that the latter group of tests are almost equivalent in power to their parametric analogs, and because of this, they state that it is preferable to use the appropriate nonparametric test if any of the assumptions of a parametric test have been saliently violated. Throughout this book it is demonstrated that in most instances when the same set of data is evaluated with both a parametric and a nonparametric test (especially a nonparametric test employing rank-order data), the two tests yield comparable results. As a general rule, in instances where only one of the two tests is significant, the parametric test is the one that is more likely to be significant. However, in most cases where a parametric test achieves significance and the nonparametric test does not, the latter test will fall just short of being significant. In instances where both tests are significant, the alpha level at which the result is significant will generally be lower for the parametric test.

3. Outliers (Test 11e: Procedures for identifying outliers) and data transformation An **outlier** is an observation (or subset of observations) in a set of data that does not appear to be consistent with the rest of the data. In most instances inconsistency is reflected in the magnitude of an observation (i.e., it is either much higher or much lower than any of the other observations). Yet what appears to be an inconsistent/extreme score to one observer may not appear to be so to another. Barnett and Lewis (1994) emphasize that a defining characteristic of an outlier is that it elicits genuine surprise in an observer. To illustrate the fact that what may surprise one observer may not surprise another, we will consider an example cited by Barnett and Lewis (1994, p. 15). The latter authors present data described by Fisher, Corbet, and Williams (1943), which represents the number of moths of a specific species that were caught in light-traps mounted in a geographical locale in England. The following 15 observations were obtained.

3, 3, 4, 5, 7, 11, 12, 15, 18, 24, 51, 54, 84, 120, 560

Barnett and Lewis (1994) point out that although the value 560 might appear to be an observation that would surprise most observers, in point of fact, it is not an anomaly. The reason why 560 would not be classified as an outlier is because an experienced entomologist would be privy to the fact that the distribution under study is characterized by a marked skewness, and consequently an occasional extreme score in the upper tail such as the value 560 is a matter-of-fact occurrence. Thus, a researcher familiar with the phenomenon under study would not classify 560 an outlier.²²

If at all possible, one should determine the source of any observation in a set of data that is viewed as anomalous, since the presence of one or more outliers can dramatically influence the values of both the mean and variance of a distribution. As a result of the latter, any test statistic computed for the data can be unreliable. As an example, assume that a researcher is comparing two groups with respect to their scores on a dependent variable, and that all the subjects in both groups except for one subject in Group 2 obtain a score between 0 and 20. The subject in Group 2 with an outlier score obtains a score of 200. It should be obvious that the presence of this one score (even if the size of the sample for Group 2 is relatively large) will inflate the mean and variance of Group 2 relative to that of Group 1, and because of this either one or both of the following consequences may result: a) A significant difference between the two group means may be obtained which would not have been obtained if the outlier score was not present in the data; and/or b) The homogeneity of variance assumption will be violated due to the higher estimated population variance computed for Group 2. By virtue of adjusting the *t* test statistic for violation of the homogeneity of variance assumption, a more conservative test will be conducted, thus making it more difficult to reject the null hypothesis.²³

Stevens (1996) notes that there are basically two strategies that can be used in dealing with outliers. One strategy is to develop and employ procedures for identifying outliers. Within the framework of the latter strategy, criteria should be established for determining under what conditions one or more scores that are identified as outliers should be deleted from a set of data. A second approach in dealing with outliers is to develop statistical procedures that are not influenced (or only minimally affected) by the presence of outliers. Such procedures are commonly called **robust statistical procedures** — the term **robust**, as noted earlier, referring to procedures which are not overly dependent on critical assumptions regarding an underlying population distribution. The discussion of outliers within the framework of robustness is predicated on the fact that their presence may lead to violation of one or more assumptions underlying a statistical test. In the case of the ***t* test for two independent samples**, the assumptions of concern are those of normality and homogeneity of variance. Although a number inferential statistical tests have been developed for identifying outliers, Sprent (1993, 1998) notes that ironically many of these tests lack robustness, and because of the latter may lack power with respect to their ability to identify the presence of one or more outliers. Sprent (1998) and Barnett and Lewis (1994) discuss the **masking effect**, which refers to the fact that a test's power in identifying a specific outlier may be compromised if there are one or more additional outliers in the data.

Barnett and Lewis (1994), who represent the most comprehensive source on the subject, describe a large number of tests for identifying outliers — they describe 48 tests alone for detection of outliers in data that are assumed to be drawn from a normal distribution. Some of the tests for identifying outliers are designed to identify a single outlier, some are designed for identification of multiple outliers, and some tests are specific with respect to identifying outliers in one or both tails of a distribution. Additionally, tests are described for detecting outliers in data that are assumed to be drawn from any number of a variety of nonnormal distributions (e.g., binomial, Poisson, gamma, exponential, etc.). Given the large number of tests that are available for detecting outliers, it is not unusual that two or more tests applied to the same set of data may not agree with one another with regard to whether a specific observation should be classified as an outlier.

Test 8e: Procedures for identifying outliers At this point we will consider some informal criteria for identifying outliers. Stevens (1996, p. 17) notes that it has been demonstrated that regardless of the distribution of data, at least $[1 - (1/k^2)](100)$ percent of the observations in a set of data must fall within k standard deviations of the mean (where k is any value greater than 1). Applying the latter, we determine that when $k = 2$, at least 75% of the observations will fall within $+2$ and -2 standard deviations from the mean. The percentages for when k is equal to 3, 4, and 5 are respectively, 88.89%, 93.75%, and 96%. These values suggest that scores which are beyond two standard deviations from the mean are rare; that scores beyond three standard deviations are even rarer; and so on. Thus, scores that yield relatively high standard deviation values should be considered as possible outliers.

Sprent (1993, 1998) discusses a procedure for identifying outliers which he describes as being relatively robust. The procedure employs Equation 11.18 to determine whether or not a score in a sample of n observations should be classified as an outlier.

$$\frac{|X_i - M|}{MAD} > Max \quad \text{(Equation 11.18)}$$

Where: X_i represents any of the n scores being evaluated with respect to whether it is an outlier
 M is the median of the n scores in the sample

MAD is the **median absolute deviation**

Max is the critical value the result to the left of the inequality must exceed in order to conclude the value X_i is an outlier

In the left side of Equation 11.18, the numerator value $|X_i - M|$ represents a difference score. The denominator value *MAD* represents a measure of dispersion.²⁴ The equation is designed to yield a standard deviation score such as that obtained by Equation I.27 (which is the equation for computing a standard deviation score for a normally distributed variable). The value *Max* on the right side of Equation 11.18 represents an extreme standard deviation score that is employed as a criterion for classifying an outlier.

The value of *MAD* in Equation 11.18 is determined as follows: a) Upon computing the sample median, obtain an absolute deviation score from the sample median for each of the n scores. The latter is done by computing the absolute value of the difference between the median and each score; b) When all n absolute deviation scores have been computed, arrange them ordinally (i.e., from lowest to highest); and c) Find the median of the n absolute deviation scores. The latter value represents the value of *MAD* to employ in Equation 11.18.

To determine whether any of the n scores in the sample is an outlier, the following protocol is employed: a) Select the score that deviates by the greatest amount from the median to initially represent the value of X_i ; b) Subtract the median from the value of X_i , and divide the difference (which will always be a positive value since it is an absolute value) by *MAD*; c) If the value obtained in b) is greater than *Max*, one can conclude that X_i is an outlier. If the value obtained in b) is equal to or less than *Max*, one cannot conclude that X_i is an outlier; d) If it is concluded that the score selected to represent X_i is not an outlier, terminate the analysis. If it is concluded that the score selected to represent X_i is an outlier, select the score that has the second greatest deviation from the median and repeat steps b) and c); and e) Continue substituting X_i values in Equation 11.18 until an X_i value is identified that is not an outlier. The reader should take note of the fact that in most cases it is assumed that few if any observations within a given sample will be identified as outliers.

Sprent (1993, p. 278) notes that the selection of the value to represent *Max* in Equation 11.18 is somewhat arbitrary. He recommends that 5 is a reasonable value to employ, since if one assumes the data are derived from an approximately normally distributed population, the value *Max* = 5 will be extremely likely to identify scores that deviate from the mean by more than three standard deviations. (From **Column 3** of **Table A1** we can determine that the likelihood of a score being greater or less than three standard deviations from the mean is .0026.) It should be noted that if there is reason to believe that the sample data are derived from a population that is not normally distributed, the choice of what value to employ to represent *Max* becomes more problematical. The reader should consult sources which discuss outliers in greater detail for a more in-depth discussion of the latter issue (e.g., Barnett and Lewis (1994) and Sprent (1993, 1998)).

To illustrate the application of Equation 11.18, assume we have a sample consisting of the following five scores: 2, 3, 4, 7, 18. Following the protocol described above: a) We determine that the median (i.e., the middle score) of the sample is 4; b) We compute the absolute deviation of each score from the median: $|2 - 4| = 2$, $|3 - 4| = 1$, $|4 - 4| = 0$, $|7 - 4| = 3$, $|18 - 4| = 14$. Arranging the four deviation scores ordinally (0, 1, 2, 3, 14), we determine the median of the five deviation scores is 2. The latter value will represent *MAD* in Equation 11.18; c) Since the only value we would suspect to be an outlier is the score of 18, we employ that value to represent X_i in Equation 11.18; d) Since we will assume the data are derived from a normal distribution, we employ the value *Max* = 5; e) Substituting the appropriate values in the left side of Equation 11.18, we compute $|18 - 4|/2 = 7$. Since the obtained value of 7 is greater than *Max* = 5, we

conclude that the score of 18 is an outlier.

When another simple test for an outlier described in Barnett and Lewis (1994, p. 247) and Tietjen (1986, pp. 500–502) is applied to the same set of data, it also yields a significant result with respect to the value 18 being an outlier. The latter test, developed by Grubbs (1969), employs Equation 11.19.

$$T_n = \frac{|X_i - \bar{X}|}{\bar{s}} \quad (\text{Equation 11.19})$$

The computed test statistic T_n is referred to as the *extreme Studentized residual*. Use of Equation 11.19 to compute T_n requires that the sample mean (which is based on all of the scores in the sample including the suspected outlier) be subtracted from the value of a suspected outlier (X_i). The resulting difference is divided by the value computed for \bar{s} (which, like the mean, is based on all the scores in the sample including the suspected outlier) with Equation I.8. The value computed for T_n is evaluated with special tables found in sources that describe the test. Employing Equation 11.19 with our data, $T_N = |18 - 6.8|/6.53 = 1.72$, which it turns out is significant at the .05 level. In spite of the fact that in the case of our example two inferential tests result in the conclusion that the observation 18 is an outlier, it is important to remember that it is not unusual for two or more tests for detecting an outlier to disagree with one another. In view of the latter, the reader is advised to consult more detailed sources (such as Barnett and Lewis (1994)) to determine the most appropriate test for detecting outliers in a given set of data.

It should be noted that employing the magnitude of a standard deviation score (i.e., a z score) as a criterion for classifying outliers can often lead to misleading conclusions. Shiffler (1988) has demonstrated that the largest possible absolute z value that can occur in a set of data is defined by the limit $(n - 1)/\sqrt{n}$. For example, if $n = 15$, the value of z cannot exceed $(15 - 1)/(\sqrt{15}) = 3.62$. Inspection of the equation $(n - 1)/\sqrt{n}$ reveals that the maximum possible absolute value z may attain is a direct function of the sample size — in other words, the larger the sample size, the larger the limiting value of z . In order to appreciate how the use of a z value with small sample sizes can lead to misleading conclusions if it is employed as a criterion for classifying outliers, consider the following examples presented by Shiffler (1988): a) A set of data consists of the following five scores: 0, 0, 0, 0, 1 million. On inspection, some researchers might immediately view the score of 1 million as an outlier. Yet when the sample mean and estimated population standard deviation are computed for the five scores, the z score associated with the score of 1 million is only $z = 1.78$; and b) A set of data is comprised of 18 scores, with 17 of the scores equal to 0 and the remaining score equal to 1. When the sample mean and estimated population standard deviation are computed for the 18 scores, the z score associated with the score of 0 is $z = 4.007$. The magnitude of the latter z value might suggest to some researchers that the score of 0 is an outlier. Thus, as noted above, when the sample size is relatively small, the theoretical limits imposed on the value of a z score may make it impractical to employ it as a criterion for classifying outliers.

Tabachnick and Fidell (1989, 1996) note that outliers present a researcher with a statistical problem if one elects to include them in the data analysis, and a moral problem if one is trying to decide whether or not to eliminate them from the analysis. In essence, how a researcher deals with outliers should depend on how one accounts for their presence. In instances where a researcher is reasonably sure that an outlier is due to any one of the following, Tabachnick and Fidell (1989, 1996) state that one has a strong argument for dropping such a score from the data: a) There is reason to believe that an error was made in recording the score in question (either human recording error or instrumentation error); b) There is reason to believe that the score is the result of failure on the part of a subject to follow instructions, or other behavior on the part of the

subject indicating a lack of cooperation and/or attention to the experiment; and c) There is reason to believe that the score is the result of failure on the part of the experimenter to employ the correct protocol in obtaining data from a subject.

One disadvantage of removing outliers from data is that it reduces the sample size, and the latter can result in a decrease in statistical power. Of course, if one is conducting a parametric test such as a *t* test, one may counteract the aforementioned loss in power by virtue of the fact that removal of an outlier will decrease the variability in the data. Tietjen (1986) notes that rejecting an outlier on a purely statistical basis may only be an indication that the data are derived from a population other than the one the researcher assumes to be the parent population. An example cited by Kruskal (1960) is employed by Tietjen (1986) to demonstrate that whether or not an observation should be considered an outlier will be a function of the hypothesis under study. The example used involves a study in which the concentration of a specific chemical in a mixture is being evaluated. Measures of the chemical are derived from five different samples, but one of the measures is way out of line in relation to the others. Let us assume that the latter measure is the result of instrumentation error. If the purpose of the study is to estimate the concentration of the chemical in the mixture, the researcher may elect to label the atypical measure an outlier, and only use the remaining four measures to compute an average value. If instead, the purpose of the study is to assess the reliability of the instrument that is employed to measure the concentration of the chemical, the outlier observation is relevant and should be retained. Kruskal (1960) emphasizes the fact that the presence of one or more outliers in a set of data may indicate something that is of practical or theoretical relevance, and because of the latter, he recommends that it should be standard protocol for researchers to report the presence of any outliers, regardless of whether or not they elect to employ them in the analysis of the data.

In the final analysis, excluding data that are deemed to be outliers is an extreme measure which entails the risk of mistakenly eliminating valid information about an underlying population.²⁵ At the other extreme, a researcher can include in the analysis all of the data, including observations that are viewed as outliers. Obviously, the latter strategy increases the likelihood that the sample will be contaminated, and therefore what may emerge from the analysis may be a gross distortion of what is true regarding the underlying population under study.

When a researcher has reservations about employing either extreme — removal of outliers versus their inclusion — an alternative strategy known as **accommodation** may be employed. The latter involves the use of a procedure which utilizes all the data, but at the same time minimizes the influence of outliers. Two obvious options within the framework of accommodation that reduce the impact of outliers are: a) Use of the median in lieu of the mean as a measure of central tendency; b) Employing an inferential statistical test that uses rank-orders instead of interval/ratio data.

Accommodation is often described within the context of employing a robust statistical procedure (e.g., a procedure that assigns weights to the different observations when calculating the sample mean). Two commonly used methods for dealing with outliers (which are sometimes discussed within the context of accommodation) are **trimming** and **Winsorization**.

Trimming data **Trimming** involves removing a fixed percentage of extreme scores from each of the tails of any of the distributions that are involved in the data analysis. As an example, in an experiment involving two groups, one might decide to omit the two highest and two lowest scores in each group (since by doing this, any outliers in either group would be eliminated). Sprent (1993) notes that common trimming levels are the top and bottom deciles (i.e., the extreme 10% from each tail of the distribution) and the first and fourth quartiles (i.e., the extreme 25% from each tail). The latter trimmed mean (i.e., the mean computed by only taking into account scores that fall in the middle 50% of the distribution) is often referred to as the **interquartile mean**. In

addition to using trimming for reducing the impact of outliers, it is also employed when a distribution has **heavy or long tails** (i.e., a relatively flat distribution with a disproportionate number of observations falling in the tails).

Winsorization Sprent (1993, p. 69) notes that the rationale underlying **Winsorization** is that the outliers may provide some useful information concerning the magnitude of scores in the distribution, but at the same time may unduly influence the results of the analysis unless some adjustment is made. Winsorization, involves replacing a fixed number of extreme scores with the score that is closest to them in the tail of the distribution in which they occur. As an example, in the distribution 0, 1, 18, 19, 23, 26, 26, 28, 33, 35, 98, 654 (which has a mean value of 80.08), one can substitute a score of 18 for both the 0 and 1 (which are the two lowest scores), and a score of 35 for the 98 and 654 (which are the two highest scores). Thus, the Winsorized distribution will be: 18, 18, 18, 19, 23, 26, 26, 28, 33, 35, 35, 35. The mean of the Winsorized distribution will be 26.17.

Barnett and Lewis (1994) note that the critical problem associated with trimming and Winsorization is selecting the number of scores that are trimmed or Winsorized. Assume that r represents the number of scores to be trimmed or Winsorized in the right tail, and that l represents the number of scores to be trimmed or Winsorized in the left tail. If $r = l$, the trimming or Winsorization process is considered **symmetric**. If $r \neq l$, the trimming or Winsorization process is considered **asymmetric**. The issue of whether a researcher believes one or both tails of a sample distribution may be contaminated is one of a number of considerations that have to be taken into account in determining the most appropriate procedure to use. In Chapter 5 of their book, Barnett and Lewis (1994) address such issues, as well as modified trimming and Winsorization procedures.

Data transformation Data transformation involves performing a mathematical operation on each of the scores in a set of data, and thereby converting the data into a new set of scores which are then employed to analyze the results of an experiment. In addition to being able to reduce the impact of outliers, a data transformation can be employed to equate heterogeneous group variances, as well as to normalize a nonnormal distribution. In point of fact, a transformation which results in homogeneity of variance, at the same time often normalizes data. Kirk (1995) and Winer *et al.* (1991) note that another reason for employing a data transformation is to insure that certain factorial designs are based on an **additive** model. A discussion of **factorial designs** and the concept of **additivity** can be found in the **between-subjects factorial analysis of variance (Test 27)**.

It is not uncommon that, as a result of a data transformation, data that will not yield a significant effect may be modified so as to be significant (or vice versa). Because of the latter, one might view a data transformation as little more than a convenient mechanism for “cooking” data until it allows a researcher to achieve a specific goal. While the latter may be true, when used judiciously, data transformation can be a valuable tool. One should consider the fact that the selection of the unit of measurement for a dependent variable will always be somewhat arbitrary. Howell (1992) cites numerous examples of transformations which are employed within various experimental settings, because of the practical or theoretical advantage they provide. Illustrative of such transformations are the use of decibels in measuring sound intensity and the Richter scale in measuring the magnitude of energy for an earthquake (both of which are based on logarithmic data transformations). Another example of a data transformation is a set of test scores which are converted into percentiles rather than reporting the original raw scores (i.e., number of items correct) for subjects.

Although, as noted earlier, a data transformation can be misused to distort data to support

a hypothesis favored by an experimenter, when employed judiciously, it can be of value. Specifically, under certain circumstances it can allow a researcher to provide a more accurate picture of the populations under study than will the analysis of untransformed data. Among those sources that describe data transformations in varying degrees of detail are Howell (1992), Kirk (1995), Myers and Well (1995), Tabachnick and Fidell (1989, 1996), Thöni (1967), and Winer *et al.* (1991). Articles by Games (1983, 1984) and Levine and Dunlap (1982, 1983) address some of the controversial issues surrounding data transformation.

Among the most commonly employed data transformations, all of which can reduce the impact of outliers (as well as normalize skewed data and/or produce homogeneity of variance), are converting scores into their **square root**, **logarithm** (a general discussion of logarithms can be found in Endnote 5 in the **Introduction**), **reciprocal**, and **arcsine**. In employing data transformations, a researcher may find it necessary to compare one or more different transformation procedures until he finds the one which best accomplishes the goal he is trying to achieve. Common sense would suggest that selection of a data transformation procedure can be based upon what it previously has been demonstrated to be successful at. In addition to the latter, Kirk (1995) recommends the following protocol for selecting a data transformation procedure: a) Apply each of the available transformation procedures to the largest and smallest scores in each of the experimental treatments/groups; b) Determine the range of values within each treatment, and compute within each treatment the ratio of the largest to the smallest value; and c) Employ the transformation procedure that yields the smallest ratio.

The most commonly employed data transformation procedures will now be discussed and demonstrated.

Square-root transformation A **square-root transformation** may be useful when the mean is proportional to the variance (i.e., the proportion between the mean of a treatment and the variance of a treatment is approximately the same for all of the treatments). Under such circumstances the square-root transformation can be effective in normalizing distributions that have a moderate positive skew, as well as making the treatment variances more homogeneous. This is the case since a square-root scale will reduced the magnitude of difference between the two tails of a positively skewed distribution by pulling the right side of the distribution in toward the middle. Reaction time is a good example of a measure in psychology that characteristically exhibits a strong positive skew (i.e., there are many fast or relatively fast reactors but there are also a few slow reactors). Consequently a square-root transformation may be able normalize a set of reaction time data. (If the square-root transformation is not successful, a logarithmic or reciprocal transformation discussed below may be more suitable for achieving this goal.) In such a case the square-root transformation can reduce skewness and stabilize distributional variance. Data taken from a Poisson distribution (discussed in Section IX (the **Addendum**) of the **binomial sign test for a single sample**) are sometimes effectively normalized with a square-root transformation. Such data typically consist of frequencies of randomly occurring objects or events that have a small probability of occurring over many trials or over a long period of time. In Poisson distributed data, the mean and variance are proportional (in fact, they are equal).

The square-root transformation is obtained through use of the equation $Y = \sqrt{X}$, where X is the original score and Y represents the transformed score. However, when any value of X is less than 10, any or all of the following equations are recommended by various sources in place of $Y = \sqrt{X}$, since they are more likely to result in homogeneous variances: a) $Y = \sqrt{X + .5}$; b) $Y = \sqrt{X} + \sqrt{X + 1}$; and c) $Y = \sqrt{X + .375}$.

Logarithmic transformation A **logarithmic transformation** may be useful when the mean is proportional to the standard deviation (i.e., the proportion between the mean of a treatment and the standard deviation of a treatment is approximately the same for all of the

treatments). Under such circumstances the logarithmic transformation can be effective in normalizing distributions that have a moderate positive skew, as well as making the treatment variances more homogeneous. Since a logarithmic transformation makes a more extreme adjustment than a square-root transformation, it can be employed to normalize distributions that have a more severe positive skew. On a logarithmic scale the distance between adjacent points on the scale will be less than the distance between the corresponding points on the original scale of measurement. As is the case with the square-root transformation, the logarithmic transformation is often useful for normalizing a dependent variable that is a measure of response time.

The logarithmic transformation is obtained through use of the equation $Y = \log X$. Since a logarithm cannot be computed for the value zero, when one or more zeros or positive numbers close to zero are present in a set of data, the following equation is employed: $Y = \log(X + 1)$. Since a logarithm cannot be computed for a negative number, a constant (the value of which is a positive number that is minimally greater than one unit above the absolute value of the lowest negative number) can be added to all of the values in a set of data, to insure that each value will be a positive number. In employing a logarithmic transformation, it does not matter what base value is employed for the logarithm — some sources employ the base 10 while others use the base $e = 2.71828$ (see Endnote 5 in the **Introduction** for a clarification of what a base value of a logarithm represents).

Reciprocal transformation A **reciprocal transformation** (also referred to as an **inverse transformation**) may be useful when the square of the mean is proportional to the standard deviation (i.e., the proportion between the square of the mean of a treatment and the standard deviation of a treatment is approximately the same for all of the treatments). Under such circumstances the reciprocal transformation can be effective in normalizing distributions that have a moderate positive skew, as well as making the treatment variances more homogeneous. Since it exerts the most extreme adjustment with regard to normality, the reciprocal transformation is often able to normalize data that the square-root and logarithmic transformations are unable to normalize. Tabachnick and Fidell (1996) recommend the reciprocal transformation for normalizing a J-shaped distribution (i.e., a distribution that looks like the letter J or its mirror image — specifically, an extremely skewed unimodal distribution that is peaked without a tail at one end, and with a tail falling off toward the other end).

The reciprocal transformation is obtained through use of the equation $Y = 1/X$. If any of the scores are equal to zero, the equation $Y = 1/(X + 1)$ should be employed. Additional comments on the reciprocal transformation can be found at the end of the discussion on data transformations.

At this point some hypothetical data will be employed to demonstrate the **square-root**, **logarithmic**, and **reciprocal transformations**. To illustrate the application of the **square-root transformation**, assume we have two groups, with five subjects per group. The interval/ratio scores of the subjects in the two groups follow: **Group 1:** 2, 3, 4, 6, 10; **Group 2:** 10, 20, 20, 25, 25. Employing Equations I.1, I.8, and I.5, the sample means, estimated population standard deviations, and estimated population variances are computed to be $\bar{X}_1 = 5$, $\bar{s}_1 = 3.16$, $\bar{s}_1^2 = 10$; $\bar{X}_2 = 20$, $\bar{s}_2 = 6.12$, $\bar{s}_2^2 = 37.5$. Note that in each group the estimated population variance is approximately two times as large as the group mean. Let us assume we wish to make the variances in the two groups more homogeneous, since the variance of Group 2 is almost four times as large as the variance of Group 1.²⁶ Since the estimated population variances and means are proportional, we elect to employ a square root transformation. Since some of the scores in Group 1 are less than 10, we will employ the equation $Y = \sqrt{X} + .5$ to convert each score. The resulting corresponding transformed scores for the subjects in the two groups are: **Group 1:** 1.581, 1.871, 2.121, 2.550, 3.240; **Group 2:** 3.240, 4.528, 4.528, 5.050, 5.050. Employing Equations I.1 and I.5 with the transformed scores, the sample means (employing the notation Y) and estimated

population variances are computed to be $\bar{Y}_1 = 2.27$, $\bar{s}_1^2 = .42$; $\bar{Y}_2 = 4.48$, $\bar{s}_2^2 = .55$. Note that the estimated population variances are now almost equal — specifically, the variance of Group 2 is only 1.31 times larger than the variance of Group 1. When the **logarithmic transformation** is applied to the same set of data (using the equation $Y = \log X$), it also results in more homogeneous variances, with the variance of Group 1 being 2.70 times larger than the variance of Group 2. On the other hand, when the **reciprocal transformation** is applied to the data, it increases heterogeneity of variance (with the reciprocal transformed variance of Group 1 being 88.89 times larger than the reciprocal transformed variance of Group 2). It would appear that the square-root transformation is the most effective in equating the variances.

To illustrate the application of the **logarithmic transformation**, assume we have two groups, with five subjects per group. The interval/ratio scores of the subjects in the two groups follow: **Group 1**: 12, 14, 16, 18, 20; **Group 2**: 28, 32, 40, 50, 50. Employing Equations I.1, I.8 and I.5, the sample means, estimated population standard deviations, and estimated population variances are computed to be $\bar{X}_1 = 16$, $\bar{s}_1 = 3.16$, $\bar{s}_1^2 = 10$; $\bar{X}_2 = 40$, $\bar{s}_2 = 10.10$, $\bar{s}_2^2 = 102$. Note that in each group the estimated population standard deviation is between one-fourth to one-fifth the size of the group mean. Let us assume we wish to make the variances in the two groups more homogeneous, since the variance of Group 2 is about ten times as large as the variance of Group 1. Since the estimated population standard deviations and means are proportional, we elect to employ a logarithmic transformation (using the equation $Y = \log X$, which employs the base 10 for the logarithm). The resulting corresponding transformed scores for the subjects in the two groups are: **Group 1**: 1.079, 1.146, 1.204, 1.255, 1.301; **Group 2**: 1.447, 1.505, 1.602, 1.699, 1.699. Employing Equations I.1 and I.5 with the transformed scores, the sample means (employing the notation \bar{Y}) and estimated population variances are computed to be $\bar{Y}_1 = 1.197$, $\bar{s}_1^2 = .008$; $\bar{Y}_2 = 1.590$, $\bar{s}_2^2 = .013$. Note that the ratio of the larger variance ($\bar{s}_2^2 = .013$) to the smaller variance ($\bar{s}_1^2 = .008$) is now only 1.68. When the **square-root transformation** is applied to the same set of data (using the equation $Y = \sqrt{X}$, since none of the scores is less than 10) it also results in more homogeneous variances, with the variance of Group 2 being 4.13 times larger than the variance of Group 1. The **reciprocal transformation** applied to the same data also results in more homogeneous variances, with the variance of Group 1 being 3.47 times larger than the variance of Group 2. It would appear that although all three transformations make the variances more homogeneous, the logarithmic transformation is the most effective.

To illustrate the application of the **reciprocal transformation**, assume we have two groups, with five subjects per group. The interval/ratio scores of the subjects in the two groups follow: **Group 1**: 2, 3, 4, 6, 10; **Group 2**: 1, 1, 3, 5, 90. Employing Equations I.1, I.8 and I.5, the sample means, estimated population standard deviations, and estimated population variances are computed to be $\bar{X}_1 = 5$, $\bar{s}_1 = 3.16$, $\bar{s}_1^2 = 10$; $\bar{X}_2 = 20$, $\bar{s}_2 = 39.17$, $\bar{s}_2^2 = 1534$. Note that in each group the square of the mean is between 8 to 10 times the size of the estimated population standard deviation. Let us assume we wish to make the variances in the two groups more homogeneous, since the variance of Group 2 is approximately 153 times as large as the variance of Group 1. Since the square of the means and the estimated standard deviations are proportional, we elect to employ a reciprocal transformation (using the equation $Y = 1/X$). The resulting corresponding transformed scores for the subjects in the two groups are: **Group 1**: .5, .333, .25, .167, .1; **Group 2**: 1, 1, .333, .2, .011. Employing Equations I.1 and I.5 with the transformed scores, the sample means and estimated population variances are computed to be $\bar{Y}_1 = .27$, $\bar{s}_1^2 = .024$; $\bar{Y}_2 = .51$, $\bar{s}_2^2 = .21$. Note that although the estimated population variances are still not equal, they are considerably closer than the values computed for the untransformed data — specifically, as a result of the transformation the variance of Group 2 is 8.92 times larger than the variance of Group 1. When the **square-root transformation** (using the equation $Y = \sqrt{X + .5}$, since some of the scores are less than 10) is applied to the same set of data, the variance of Group

2 is 29.92 times larger than the variance of Group 1. When the **logarithmic transformation** is applied to the same set of data (using the equation $Y = \log X$), the variance of Group 2 is 8.8 times larger than the variance of Group 1. It would appear that although none of the three transformations is able to result in homogeneous group variances, the logarithmic and reciprocal transformations come closest to achieving that goal. In the case of this latter example, the score of 90 in Group 2 would appear to be a possible outlier, and, as such, might not be included in the data or have its impact altered in some way through use of some method of accommodation designed to reduce the impact of an outlier. It should also be noted that use of the degree of proportionality between the means, squared means, standard deviations, and/or variances will not be the only factors that can be employed to determine what transformation will be most effective. Often, through use of trial and error, a researcher can investigate which, if any, transformation will best achieve the desired goal.

Arcsine (arcsin) transformation An **arcsine transformation** (also referred to as an **angular** or **inverse sine transformation**) involves the use of a trigonometric function which is able to transform a proportion between 0 and 1 (or percentage between 0% and 100%) into an angle expressed in radians (1 radian = 57.3 degrees, which is equal to $180^\circ/\pi$, and one degree equals .01745 radians). The arcsine of a number is the angle whose sine is that number. Although some books contain tables of arcsine values, an arcsine can be computed on many calculators through use of the \sin^{-1} key. An arcsine transformation may be useful for normalizing distributions when the means and variances are proportional, and the distributions are binomially distributed. Howell (1992) notes that although both the square-root and arcsine transformations are suitable when the means and variances are proportional, whereas the square-root transformation compresses the upper tail of the distribution, the arcsine transformation flattens the distribution by stretching out both tails.

The arcsine transformation is obtained through use of the equation $Y = 2 \arcsin\sqrt{X}$, where X will be a proportion between 0 and 1. Based on a paper by Bartlett (1947), sources recommend that the equation $Y = 2 \arcsin\sqrt{X + (1/2n)}$ (or $Y = 2 \arcsin\sqrt{X + (1/4n)}$) be employed when the value of X is equal to 0, and that the equation $Y = 2 \arcsin\sqrt{X - (1/2n)}$ (or $Y = 2 \arcsin\sqrt{X - (1/4n)}$) be employed when the value of X is equal to 1 (where n is the number of observations in the treatment for which a proportion is computed). All of the aforementioned equations yield a value of Y that is expressed in radians. To illustrate the arcsine transformation, assume we have the following five values which represent the proportion of bulbs that bloom in each of five flower beds: .25, .39, .5, .68, .75. When the latter values are employed in the equation $Y = 2 \arcsin\sqrt{X}$, the following values (in radians) are computed for Y : 1.0472, 1.3490, 1.5708, 1.9391, 2.0944. The possible range of values that Y can equal, through use of any of the equations noted above, is 0 radians (for a proportion of zero) to 3.1416 radians (for a proportion of 1) (which is equal to π).

Some sources (e.g., Myers and Well (1995), Rao (1998) and Zar (1999)) employ the following alternative arcsine transformation equation which expresses the value of Y in degrees: $Y = \arcsin\sqrt{X}$. At the conclusion of the data analysis, the transformed values can be converted back into the original proportions through use of the equation $X = (\sin Y)^2$. To illustrate the arcsine transformation using the alternative equation, assume we have the same five values representing the proportion of bulbs that bloom in each of five flower beds (i.e., .25, .39, .5, .68, .75). When the latter values are employed in the equation $Y = \arcsin\sqrt{X}$, the following values (in degrees) are computed for Y : 30, 38.65, 45, 55.55, 60.²⁷ Zar (1999) notes additional alternative equations for computing the value of Y in degrees. The possible range of values that Y can equal, through use of any of the equations that compute an arcsine in degrees, is 0° (for a proportion of zero) to 90° (for a proportion of 1). Additional information on the arcsine

transformation, as well as examples illustrating its application, can be found in Rao (1998) and Zar (1999).

$Y = X^2$ transformation Zar (1999) notes that if there is an inverse relationship between the treatment standard deviations and the treatment means (i.e., as the standard deviations increase, the means decrease) and/or a distribution is negatively skewed, the following transformation may be useful for normalizing data and creating homogeneity of variance: $Y = X^2$.

Final comments on data transformation Some data transformations, such as a reciprocal transformation, may result in a reversal in the direction of the scores. In other words, if we have two scores a and b with $a > b$, if we obtain the reciprocal of both, the reciprocal of b will be greater than the reciprocal of a . The process of reversing the direction to restore the original ordinal relationship between the scores is called **reflection**. Reflection can also be used to convert negatively skewed data into positively skewed data. Tabachnick and Fidell (1996) note the latter can be accomplished by doing the following: a) Create a constant that is larger than all of the scores in a distribution by adding the value 1 to the largest score in the distribution; b) Subtract each score in the distribution from the constant value. At this point the converted data will have a positive skew and the appropriate transformation for normalizing positively skewed data (e.g., square-root, logarithmic, and reciprocal transformations) can be employed. After the appropriate statistical test has been employed with the normalized data, the researcher must remember to take into account the reversal in the direction of scoring in interpreting the results.

In the final analysis, as with anything else, a data transformation should be judged on the basis of its practical consequences. Specifically, if through use of a data transformation a significant result is obtained, and that result can be consistently replicated employing the same data transformation, a researcher can conclude that one is dealing with a reliable phenomenon. If the data obtained through use of a data transformation proves to be useful in a practical or theoretical sense, it is as valuable as data which when analyzed does not require any sort of transformation.

4. Hotelling's T^2 The **multivariate** analog of the t test for two independent samples is **Hotelling's T^2** (Hotelling (1931)), which is one of a number multivariate statistical procedures discussed in the book. The term multivariate is employed in reference to procedures that evaluate experimental designs in which there are multiple independent variables and/or multiple dependent variables. **Hotelling's T^2** , which is a special case of the **multivariate analysis of variance (MANOVA)** (discussed in Section VII of the **single-factor between-subjects analysis of variance**), can be employed to analyze the data for an experiment that involves a single independent variable comprised of two levels and multiple dependent variables. With regard to the latter, instead of a single score, each subject produces scores on two or more dependent variables. To illustrate, let us assume that in Example 11.1 two scores are obtained for each subject. One score represents a subject's level of depression and a second score represents the subject's level of anxiety. Within the framework of **Hotelling's T^2** , a composite mean based on both the depression and anxiety scores of subjects is computed for each group. The latter composite means are referred to as **mean vectors** or **centroids**. As is the case with the t test for two independent samples, the means (in this case composite) for the two groups are then compared with one another. For a discussion of the advantages of employing multiple dependent variables in a study, the reader should refer to the discussion of the **multivariate analysis of variance** in Section VII of the **single-factor between-subjects analysis of variance**). Like most multivariate procedures, the mathematics involved in conducting **Hotelling's T^2** is quite complex, and for this reason it becomes laborious if not impractical to implement without the aid of a computer. Since a full description of **Hotelling's T^2** is beyond the scope of this book, the interested reader should

consult sources such Stevens (1986, 1996) and Tabachnick and Fidell (1989, 1996) which describe multivariate procedures in detail.

VIII. Additional Examples Illustrating the Use of the t Test for Two Independent Samples

Two additional examples that can be evaluated with the t test for two independent samples are presented in this section. Since Examples 11.4 and 11.5 employ the same data set as that employed in Example 11.1, they yield the identical result.

Example 11.4 *A researcher wants to assess the relative effect of two different kinds of punishment (loud noise versus a blast of cold air) on the emotionality of mice. Each of ten mice is randomly assigned to one of two groups. During the course of the experiment each mouse is sequestered in an experimental chamber. While in the chamber, each of the five mice in Group 1 is periodically presented with a loud noise, and each of the five mice in Group 2 is periodically presented with a blast of cold air. The presentation of the punitive stimulus for each of the animals is generated by a machine that randomly presents the stimulus throughout the duration of the time the mouse is in the chamber. The dependent variable of emotionality employed in the study is the number of times each mouse defecates while in the experimental chamber. The number of episodes of defecation for the 10 mice follow: **Group 1:** 11, 1, 0, 2, 0; **Group 2:** 11, 11, 5, 8, 4. Do subjects exhibit differences in emotionality under the different experimental conditions?*

In Example 11.4, if the one-tailed alternative hypothesis $H_1: \mu_1 < \mu_2$ is employed it can be concluded that the group presented the blast of cold air (Group 2) obtains a significantly higher emotionality score than the group presented with loud noise (Group 1). This is the case, since the computed value $t = -1.96$ indicates that the average defecation score of Group 2 is significantly higher than the average defecation score of Group 1. As is the case in Example 11.1, the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is not supported, and thus, if the latter alternative hypothesis is employed one cannot conclude that the blast of cold air results in higher emotionality.

Example 11.5 *Each of two companies that manufacture the same size precision ball bearing claims it has better quality control than its competitor. A quality control engineer conducts a study in which he compares the precision of ball bearings manufactured by the two companies. The engineer randomly selects five ball bearings from the stock of Company A and five ball bearings from the stock of Company B. He measures how much the diameter of each of the ten ball bearings deviates from the manufacturer's specifications. The deviation scores (in micrometers) for the ten ball bearings manufactured by the two companies follow: **Company A:** 11, 1, 0, 2, 0; **Company B:** 11, 11, 5, 8, 4. What can the engineer conclude about the relative quality control of the two companies?*

In Example 11.5, if the one-tailed alternative hypothesis $H_1: \mu_1 < \mu_2$ is employed it can be concluded that Company B obtains a significantly higher deviation score than Company A. This will allow the researcher to conclude that Company A has superior quality control. As is the case in Example 11.1, the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is not supported, and thus, if the latter alternative hypothesis is employed, the researcher cannot conclude that Company A has superior quality control.

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Endnotes

1. Alternative terms that are commonly used to describe the different samples employed in an experiment are **groups**, **experimental conditions**, and **experimental treatments**.

2. It should be noted that there is a design in which different subjects serve in each of the k experimental conditions that is categorized as a **dependent samples design**. In a **dependent samples design** each subject either serves in all of the k experimental conditions, or else is matched with a subject in each of the other $(k - 1)$ experimental conditions. When subjects are matched with one another they are equated on one or more variables that are believed to be correlated with scores on the dependent variable. The concept of matching and a general discussion of the **dependent sample design** can be found under the **t test for two dependent samples (Test 17)**.
3. An alternative but equivalent way of writing the null hypothesis is $H_0: \mu_1 - \mu_2 = 0$. The analogous alternative but equivalent ways of writing the alternative hypotheses in the order they are presented are: $H_1: \mu_1 - \mu_2 \neq 0$, $H_1: \mu_1 - \mu_2 > 0$, $H_1: \mu_1 - \mu_2 < 0$.
4. In order to be solvable, an equation for computing the t statistic requires that there is variability in the scores of at least one of the two groups. If all subjects in Group 1 have the same score and all subjects in Group 2 have the same score, the values computed for the estimated population variances will equal zero (i.e., $\hat{s}_1^2 = \hat{s}_2^2 = 0$). If the latter is true the denominator of any of the equations to be presented for computing the value of t will equal zero, thus rendering a solution impossible.
5. When $n_1 = n_2$, $\hat{s}_p = \sqrt{(\hat{s}_1^2 + \hat{s}_2^2)/2}$.
6. The actual value that is estimated by $s_{\bar{X}_1 - \bar{X}_2}$ is $\sigma_{\bar{X}_1 - \bar{X}_2}$, which is the standard deviation of the sampling distribution of the difference scores for the two populations. The meaning of the **standard error of the difference** can be best understood by considering the following procedure for generating an empirical sampling distribution of difference scores: a) Obtain a random sample of n_1 scores from Population 1 and a random sample of n_2 scores from Population 2; b) Compute the mean of each sample; c) Obtain a difference score by subtracting the mean of Sample 2 from the mean of Sample 1 — i.e., $\bar{X}_1 - \bar{X}_2 = D$; and d) Repeat steps a) through c) m times. At the conclusion of this procedure one will have obtained m difference scores. The **standard error of the difference** represents the standard deviation of the m difference scores, and can be computed by using Equation I.8/2.1. Thus: $s_{\bar{X}_1 - \bar{X}_2} = \sqrt{[(\sum D^2 - ((\sum D)^2/m)]/[m - 1]}$. The standard deviation that is computed with the aforementioned equation is an estimate of $\sigma_{\bar{X}_1 - \bar{X}_2}$.
7. Equation 11.4 can also be written in the form $df = (n_1 - 1) + (n_2 - 1)$, which reflects the number of degrees of freedom for each of the groups.
8. The absolute value of t is employed to represent t in the summary statement.
9. The F_{\max} test is one of a number of statistical procedures that are named after the English statistician Sir Ronald Fisher. Among Fisher's contributions to the field of statistics was the development of a sampling distribution referred to as the F distribution (which bears the first letter of his surname). The values in the F_{\max} distribution are derived from the F distribution.
10. A tabled $F_{.975}$ value is the value below which 97.5% of the F distribution falls and above which 2.5% of the distribution falls. A tabled $F_{.995}$ value is the value below which 99.5% of the F distribution falls and above which .5% of the distribution falls.

11. In **Table A9** the value $F_{\max, .01} = 23.2$ is the result of rounding off $F_{.995} = 23.15$.
12. A tabled $F_{.025}$ value is the value below which 2.5% of the F distribution falls and above which 97.5% of the distribution falls. A tabled $F_{.005}$ value is the value below which .5% of the F distribution falls and above which 99.5% of the distribution falls.
13. Most sources only list values in the upper tail of the F distribution. The values $F_{.05} = .157$ and $F_{.01} = .063$ are obtained from Guenther (1965). It so happens that when $df_{\text{num}} = df_{\text{den}}$, the value of $F_{.05}$ can be obtained by dividing 1 by the value of $F_{.95}$. Thus: $1/6.39 = .157$. In the same respect the value of $F_{.01}$ can be obtained by dividing 1 by the value of $F_{.99}$. Thus: $1/15.98 = .063$.
14. When $n = n_1 = n_2$ and $t' = t_1 = t_2$, the t' value computed with Equation 11.9 will equal the tabled critical t value for $df = n - 1$. When $n_1 \neq n_2$, the computed value of t' will fall in between the values of t_1 and t_2 . It should be noted, that the effect of violation of the homogeneity of variance assumption on the t test statistic decreases as the number of subjects employed in each of the samples increases. This can be demonstrated in relation to Equation 11.9, in that if there are a large number of subjects in each group the value that is employed for both t_1 and t_2 in Equation 11.9 is $t_{.05} = 1.96$. The latter tabled critical two-tailed .05 value, which is also the tabled critical two-tailed .05 value for the normal distribution, is the value that is computed for t' . Thus, in the case of large sample sizes the tabled critical value for $df = n_1 + n_2 - 2$ will be equivalent to the value computed for $df = n_1 - 1$ and $df = n_2 - 1$.
15. The **treatment effect** described in this section is not the same thing as **Cohen's d index** (the **effect size** computed with Equation 11.10). However, if a hypothesized effect size is present in a set of data, the computed value of d can be used as a measure of treatment effect. In such an instance, the value of d will be positively correlated with the value of the treatment effect described in this section. Cohen (1988, pp. 24–27) describes how the **d index** can be converted into the type of correlational treatment effect measure that is discussed in this section. Endnote 18 discusses the relationship between the **d index** and the **omega squared** statistic presented in this section in more detail.
16. It should be noted, however, that the degree of error associated with a measure of treatment effect will decrease as the size of the sample employed to compute the measure increases.
17. The reader familiar with the concept of correlation can think of a measure of treatment effect as a correlational measure which provides information analogous to that provided by the **coefficient of determination** (designated by the notation r^2), which is the square of the **Pearson product-moment correlation coefficient**. The **coefficient of determination** (which is discussed in more detail in Section V of the **Pearson product-moment correlation coefficient**) measures the degree of variability on one variable that can be accounted for by variability on a second variable. This latter definition is consistent with the definition that is provided in this section for a treatment effect.
18. a) In actuality, Cohen (1977, 1988) employs the notation for **eta squared** (which is discussed briefly in the next paragraph and in greater detail in Section VI of the **single-factor between-subjects analysis of variance**) in reference to the aforementioned effect size values. Endnote 58 in the **single-factor between-subjects analysis of variance** clarifies

Cohen's (1977, 1988) use of **eta squared** and **omega squared** to represent the same measure; b) Cohen (1977, 1988, pp. 23–27) states that the small, medium, and large effect size values of .0099, .0588, and .1379, are equivalent to the values .2, .5, and .8 for his ***d* index** (which was discussed previously in the section on statistical power). In point of fact, the values .2, .5, and .8 represent the minimum values for a small, medium, and large effect size for **Cohen's *d* index**. The conversion of an **omega squared/eta squared** value into the corresponding **Cohen's *d* index** value is described in Section IX (the **Addendum**) of the **Pearson product-moment correlation coefficient** under the discussion of **meta-analysis and related topics**.

19. This result can also be written as: $-.89 \leq (\mu_2 - \mu_1) \leq 10.89$.
20. In instances where, in stating the null hypothesis, a researcher stipulates that the difference between the two population means is some value other than zero, the numerator of Equation 11.16 is the same as the numerator of Equation 11.5. The protocol for computing the value of the numerator is identical to that employed for Equation 11.5.
21. The general issues discussed in this section are relevant to any case in which a parametric and nonparametric test can be employed to evaluate the same set of data.
22. Barnett and Lewis (1994) note that the presence of an outlier may not always be obvious as a result of visual inspection of data. Typically, the more complex the structure of data, the more difficult it becomes to visually detect outliers. Regression analysis and multivariate analysis are cited as examples of data analysis where visual detection of outliers is often difficult.
23. If, as a result of the presence of one or more outliers, the difference between the group means is also inflated, the use of a more conservative test will, in part, compensate for this latter effect. The impact of outliers on the ***t* test for two independent samples** is discussed by Zimmerman and Zumbo (1993). The latter authors note that the presence of outliers in a sample may decrease the power of the ***t* test** to such a degree that the **Mann-Whitney *U* test** (which is the rank-order nonparametric analog of the ***t* test for two independent samples**) will be a more powerful test for comparing two independent samples.
24. Barnett and Lewis (1994, p. 84) note that the use of the **median absolute deviation** as a measure of dispersion/variability can be traced back to the 19th century to the great German mathematician, Johann Karl Friedrich Gauss. Barnett and Lewis (1994, p. 156) state that although the **median absolute deviation** is a less efficient measure of dispersion than the standard deviation, it is a more robust estimator (especially for nonnormally distributed data).
25. Samples in which data have been deleted or modified are sometimes referred to as **censored samples** (Barnett and Lewis (1994, p. 78). The term **censoring**, however, is most commonly employed in reference to studies where scores are not available for some of the subjects, since it is either not desirable or possible to follow each subject until the conclusion of a study. This latter type of censored data is most commonly encountered in medical research when subjects no longer make themselves available for study, or a researcher is unable to locate subjects beyond a certain period of time. Good (1994, p. 117) notes that another example of censoring occurs when, within the framework of evaluating

a variable, the measurement breaks down at some point on the measurement continuum (usually at an extreme point). Consequently, one must employ approximate scores instead of exact scores to represent the observations that cannot be measured with precision. Two obvious options that can be employed to negate the potential impact of censored data are: a) Use of the median in lieu of the mean as a measure of central tendency; and b) Employing an inferential statistical test that uses rank-orders instead of interval/ratio scores.

Among the sources that describe ways of dealing with censored data are Good (1994), Hollander and Wolfe (1999), Pagano and Gauvreau (1993), and Rosner (1995). The latter three references all discuss the **Kaplan–Meier method/product-limit estimator** (1958), which is a procedure that deals with censored data in estimating survival probabilities within the framework of medical research. Sprent (1993) also discusses censored data within the context of describing the **Gehan–Wilcoxon test for censored data** (developed by Gehan (1965a, 1965b)), a procedure for evaluating censored data in a design involving two independent samples.

26. In this example, as well as other examples in this section, use of the F_{\max} test may not yield a significant result (i.e., it may not result in the conclusion that the population variances are heterogeneous). The intent of the examples, however, is only to illustrate the variance stabilizing properties of the transformation methods.
27. If the relationship 1 radian = 57.3 degrees is applied for a specific proportion, the number of degrees computed with the equation $Y = \arcsin\sqrt{X}$ will not correspond to the number of radians computed with the equation $Y = 2 \arcsin\sqrt{X}$. Nevertheless, if the transformed data derived from the two equations are evaluated with the same inferential statistical test, the same result is obtained. In point of fact, if the equation $Y = \arcsin\sqrt{X}$ is employed to derive the value of Y in radians, and the resulting value is multiplied by 57.3, it will yield the same number of degrees obtained when that equation is used to derive the value of Y in degrees. Since the multiplication of $\arcsin\sqrt{X}$ by 2 in the equation $Y = 2 \arcsin\sqrt{X}$ does not alter the value of the ratio for the difference between means versus pooled variability (or other relevant parameters being estimated within the framework of a statistical test), it yields the same test statistic regardless of which equation is employed. The author is indebted to Jerrold Zar for clarifying the relationship between the arcsine equations.

Test 12

Mann–Whitney U Test

(Nonparametric Test Employed with Ordinal Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test Do two independent samples represent two populations with different median values (or different distributions with respect to the rank-orderings of the scores in the two underlying population distributions)?

Relevant background information on test The **Mann–Whitney U test** is employed with ordinal (rank-order) data in a hypothesis testing situation involving a design with two independent samples. If the result of the **Mann–Whitney U test** is significant, it indicates there is a significant difference between the two sample medians, and as a result of the latter the researcher can conclude there is a high likelihood that the samples represent populations with different median values.

Two versions of the test to be described under the label of the **Mann–Whitney U test** were independently developed by Mann and Whitney (1947) and Wilcoxon (1949). The version to be described here is commonly identified as the **Mann–Whitney U test**, while the version developed by Wilcoxon (1949) is usually referred to as the **Wilcoxon–Mann–Whitney test**.¹ Although they employ different equations and different tables, the two versions of the test yield comparable results. In employing the **Mann–Whitney U test**, one of the following is true with regard to the rank-order data that are evaluated: a) The data are in a rank-order format, since it is the only format in which scores are available; or b) The data have been transformed into a rank-order format from an interval/ratio format, since the researcher has reason to believe that the normality assumption (as well as, perhaps, the homogeneity of variance assumption) of the **t test for two independent samples (Test 11)** (which is the parametric analog of the **Mann–Whitney U test**) is saliently violated. It should be noted that when a researcher elects to transform a set of interval/ratio data into ranks, information is sacrificed. This latter fact accounts for why there is reluctance among some researchers to employ nonparametric tests such as the **Mann–Whitney U test**, even if there is reason to believe that one or more of the assumptions of the **t test for two independent samples** have been violated.

Various sources (e.g., Conover (1980, 1999), Daniel (1990), and Marascuilo and McSweeney (1977)) note that the **Mann–Whitney U test** is based on the following assumptions: a) Each sample has been randomly selected from the population it represents; b) The two samples are independent of one another; c) The original variable observed (which is subsequently ranked) is a continuous random variable. In truth, this assumption which is common to many nonparametric tests, is often not adhered to, in that such tests are often employed with a dependent variable that represents a discrete random variable; and d) The underlying distributions from which the samples are derived are identical in shape. The shapes of the underlying population distributions, however, do not have to be normal. Maxwell and Delaney (1990) point out the assumption of identically shaped distributions implies equal dispersion of data within each distribution. Because of this, they note that like the **t test for two independent samples**, the

Mann–Whitney U test also assumes homogeneity of variance with respect to the underlying population distributions. Because the latter assumption is not generally acknowledged for the **Mann–Whitney U test**, it is not uncommon for sources to state that violation of the homogeneity of variance assumption justifies use of the **Mann–Whitney U test** in lieu of the **t test for two independent samples**. It should be pointed out, however, that there is some empirical evidence which suggests that the sampling distribution for the **Mann–Whitney U test** is not as affected by violation of the homogeneity of variance assumption as is the sampling distribution for **t test for two independent samples**. One reason cited by various sources for employing the **Mann–Whitney U test**, is that by virtue of ranking interval/ratio data a researcher will be able to reduce or eliminate the impact of **outliers**. As noted in Section VII of the **t test for two independent samples**, since **outliers** can dramatically influence variability, they can be responsible for heterogeneity of variance between two or more samples. In addition, **outliers** can have a dramatic impact on the value of a sample mean.

II. Example

Example 12.1 is identical to Example 11.1 (which is evaluated with the **t test for two independent samples**). In evaluating Example 12.1 it will be assumed that the interval/ratio data are rank-ordered, since one or more of the assumptions of the **t test for two independent samples** have been saliently violated.

Example 12.1 *In order to assess the efficacy of a new antidepressant drug, ten clinically depressed patients are randomly assigned to one of two groups. Five patients are assigned to Group 1, which is administered the antidepressant drug for a period of six months. The other five patients are assigned to Group 2, which is administered a placebo during the same six-month period. Assume that prior to introducing the experimental treatments, the experimenter confirmed that the level of depression in the two groups was equal. After six months elapse all ten subjects are rated by a psychiatrist (who is blind with respect to a subject's experimental condition) on their level of depression. The psychiatrist's depression ratings for the five subjects in each group follow (the higher the rating, the more depressed a subject): **Group 1:** 11, 1, 0, 2, 0; **Group 2:** 11, 11, 5, 8, 4. Do the data indicate that the antidepressant drug is effective?*

III. Null versus Alternative Hypotheses

Null hypothesis $H_0: \theta_1 = \theta_2$

(The median of the population Group 1 represents equals the median of the population Group 2 represents. With respect to the sample data, when both groups have an equal sample size, this translates into the sum of the ranks of Group 1 being equal to the sum of the ranks of Group 2 (i.e., $\sum R_1 = \sum R_2$). A more general way of stating this, which also encompasses designs involving unequal sample sizes, is that the means of the ranks of the two groups are equal (i.e., $R_1 = R_2$).

Alternative hypothesis $H_1: \theta_1 \neq \theta_2$

(The median of the population Group 1 represents does not equal the median of the population Group 2 represents. With respect to the sample data, when both groups have an equal sample size, this translates into the sum of the ranks of Group 1 not being equal to the sum of the ranks of Group 2 (i.e., $\sum R_1 \neq \sum R_2$). A more general way of stating this, which also encompasses designs involving unequal sample sizes, is that the means of the ranks of the two groups are not

equal (i.e., $\bar{R}_1 \neq \bar{R}_2$). This is a **nondirectional alternative hypothesis** and it is evaluated with a **two-tailed test**.)

or

$$H_1: \theta_1 > \theta_2$$

(The median of the population Group 1 represents is greater than the median of the population Group 2 represents. With respect to the sample data, when both groups have an equal sample size (so long as a rank of 1 is given to the lowest score), this translates into the sum of the ranks of Group 1 being greater than the sum of the ranks of Group 2 (i.e., $\sum R_1 > \sum R_2$). A more general way of stating this (which also encompasses designs involving unequal sample sizes) is that the mean of the ranks of Group 1 is greater than the mean of the ranks of Group 2 (i.e., $\bar{R}_1 > \bar{R}_2$). This is a **directional alternative hypothesis** and it is evaluated with a **one-tailed test**.)

or

$$H_0: \theta_1 < \theta_2$$

(The median of the population Group 1 represents is less than the median of the population Group 2 represents. With respect to the sample data, when both groups have an equal sample size (so long as a rank of 1 is given to the lowest score), this translates into the sum of the ranks of Group 1 being less than the sum of the ranks of Group 2 (i.e., $\sum R_1 < \sum R_2$). A more general way of stating this (which also encompasses designs involving unequal sample sizes) is that the mean of the ranks of Group 1 is less than the mean of the ranks of Group 2 (i.e., $\bar{R}_1 < \bar{R}_2$). This is a **directional alternative hypothesis** and it is evaluated with a **one-tailed test**.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis is rejected.

IV. Test Computations

The data for Example 12.1 are summarized in [Table 12.1](#). The total number of subjects employed in the experiment is $N = 10$. There are $n_1 = 5$ subjects in Group 1 and $n_2 = 5$ subjects in Group 2. The original interval/ratio scores of the subjects are recorded in the columns labelled X_1 and X_2 . The adjacent columns R_1 and R_2 contain the rank-order assigned to each of the scores. The rankings for Example 12.1 are summarized in [Table 12.2](#). The ranking protocol for the **Mann-Whitney U test** is described in this section. Note that in [Table 12.1](#) and [Table 12.2](#) each subject's identification number indicates the order in [Table 12.1](#) in which a subject's score appears in a given group, followed by his/her group. Thus, Subject i, j is the i^{th} subject in Group j .

The following protocol, which is summarized in [Table 12.2](#), is used in assigning ranks.

a) All $N = 10$ scores are arranged in order of magnitude (irrespective of group membership), beginning on the left with the lowest score and moving to the right as scores increase. This is done in the second row of [Table 12.2](#).

b) In the third row of [Table 12.2](#), all $N = 10$ scores are assigned a rank. Moving from left to right, a rank of 1 is assigned to the score that is furthest to the left (which is the lowest score), a rank of 2 is assigned to the score that is second from the left (which, if there are no ties, will be the second lowest score), and so on until the score at the extreme right (which will be the highest score) is assigned a rank equal to N (if there are no ties for the highest score).

c) The ranks in the third row of [Table 12.2](#) must be adjusted when there are tied scores present in the data. Specifically, in instances where two or more subjects have the same score,

Table 12.1 Data for Example 12.1

Group 1			Group 2		
	X_1	R_1		X_2	R_2
Subject 1,1	11	9	Subject 1,2	11	9
Subject 2,1	1	3	Subject 2,2	11	9
Subject 3,1	0	1.5	Subject 3,2	5	6
Subject 4,1	2	4	Subject 4,2	8	7
Subject 5,1	0	1.5	Subject 5,2	4	5
$\Sigma R_1 = 19$			$\Sigma R_2 = 36$		
$\bar{R}_1 = \frac{\Sigma R_1}{n_1} = \frac{19}{5} = 3.8$			$\bar{R}_2 = \frac{\Sigma R_2}{n_2} = \frac{36}{5} = 7.2$		

Table 12.2 Rankings for the Mann–Whitney U Test for Example 12.1

Subject identification number	3,1	5,1	2,1	4,1	5,2	3,2	4,2	1,1	1,2	2,2
Depression score	0	0	1	2	4	5	8	11	11	11
Rank prior to tie adjustment	1	2	3	4	5	6	7	8	9	10
Tie-adjusted rank	1.5	1.5	3	4	5	6	7	9	9	9

the average of the ranks involved is assigned to all scores tied for a given rank. This adjustment is made in the fourth row of Table 12.2. To illustrate: Both Subjects 3,1 and 5,1 have a score of 0. Since the two scores of 0 are the lowest scores out of the total of ten scores, in assigning ranks to these scores we can arbitrarily assign one of the 0 scores a rank of 1 and the other a rank of 2. However, since both of these scores are identical it is more equitable to give each of them the same rank. To do this, we compute the average of the ranks involved for the two scores. Thus, the two ranks involved prior to adjusting for ties (i.e., the ranks 1 and 2) are added up and divided by two. The resulting value $(1 + 2)/2 = 1.5$ is the rank assigned to each of the subjects who is tied for 0. There is one other set of ties present in the data which involves three subjects. Subjects 1,1, 1,2, and 2,2 all obtain a score of 11. Since the ranks assigned to these three scores prior to adjusting for ties are 8, 9, and 10, the average of the three ranks $(8 + 9 + 10)/3 = 9$ is assigned to the scores of each of the three subjects who obtain a score of 11.

Although it is not the case in Example 12.1, it should be noted that any time each set of ties involves subjects in the same group, the tie adjustment will result in the identical sum and average for the ranks of the two groups that will be obtained if the tie adjustment is not employed. Because of this, under these conditions the computed test statistic will be identical regardless of whether or not one uses the tie adjustment. On the other hand, when one or more sets of ties involve subjects from both groups, the tie-adjusted ranks will yield a value for the test statistic that will be different from that which will be obtained if the tie adjustment is not employed. In Example 12.1, although the two subjects who obtain a score of zero happen to be in the same group, in the case of the three subjects who have a score of 11, one subject is in Group 1 and the other two subjects are in Group 2.

If the ranking protocol described in this section is used with Example 12.1, and the researcher elects to employ a one-tailed alternative hypothesis, the directional alternative hypothesis $H_1: \theta_1 < \theta_2$ is employed. The latter directional alternative hypothesis is employed, since it predicts that Group 1, the group that receives the antidepressant, will have a lower median score, and thus a lower sum of ranks/average rank (both of which are indicative of a lower level of depression) than Group 2.

It should be noted that it is permissible to reverse the ranking protocol described in this section. Specifically, one can assign a rank of 1 to the highest score, a rank of 2 to the second highest score, and so on, until reaching the lowest score which is assigned a rank equal to the value of N . Although this reverse ranking protocol will yield the identical **Mann–Whitney test** statistic as the ranking protocol described in this section, it will result in ranks that are the opposite of those obtained in [Table 12.2](#). If the protocol employed in ranking is taken into account in interpreting the results of the **Mann–Whitney U test**, both ranking protocols will lead to identical conclusions. Since it is less likely to cause confusion in interpreting the test statistic, it is recommended that the original ranking protocol described in this section be employed — i.e., assigning a rank of 1 to the lowest score and a rank equivalent to the value of N to the highest score. In view of this, in all future discussion of the **Mann–Whitney U test**, as well as other tests that involve rank-ordering data, it will be assumed (unless otherwise stipulated) that the ranking protocol employed assigns a rank of 1 to the lowest score and a rank of N to the highest score.

Once all of the subjects have been assigned a rank, the sum of the ranks for each of the groups is computed. These values, $\Sigma R_1 = 19$ and $\Sigma R_2 = 36$, are computed in [Table 12.1](#). Upon determining the sum of the ranks for both groups, the values U_1 and U_2 are computed employing Equations 12.1 and 12.2.

$$U_1 = n_1 n_2 + \frac{n_1(n_1 + 1)}{2} - \Sigma R_1 \quad \text{(Equation 12.1)}$$

$$U_2 = n_1 n_2 + \frac{n_2(n_2 + 1)}{2} - \Sigma R_2 \quad \text{(Equation 12.2)}$$

Employing Equations 12.1 and 12.2, the values $U_1 = 21$ and $U_2 = 4$ are computed.

$$U_1 = (5)(5) + \frac{5(5 + 1)}{2} - 19 = 21$$

$$U_2 = (5)(5) + \frac{5(5 + 1)}{2} - 36 = 4$$

Note that U_1 and U_2 can never be negative values. If a negative value is obtained for either, it indicates an error has been made in the rankings and/or calculations.

Equation 12.3 can be employed to confirm that the correct values have been computed for U_1 and U_2 .

$$n_1 n_2 = U_1 + U_2 \quad \text{(Equation 12.3)}$$

If the relationship in Equation 12.3 is not confirmed, it indicates that an error has been made in ranking the scores or in the computation of the U values. The relationship described by Equation 12.3 is confirmed below for Example 12.1.

$$(5)(5) = 21 + 4 = 25$$

V. Interpretation of the Test Results

The smaller of the two values U_1 versus U_2 is designated as the obtained U statistic. Since $U_2 = 4$ is smaller than $U_1 = 21$, the value of $U = 4$. The value of U is evaluated with [Table A11 \(Table of Critical Values for the Mann–Whitney \$U\$ Statistic\)](#) in the [Appendix](#). In [Table](#)

A11, the critical U values are listed in reference to the number of subjects in each group.² For $n_1 = 5$ and $n_2 = 5$, the tabled critical two-tailed .05 and .01 values are $U_{.05} = 2$ and $U_{.01} = 0$, and the tabled critical one-tailed .05 and .01 values are $U_{.05} = 4$ and $U_{.01} = 1$. In order to be significant, the obtained value of U must be **equal to or less than** the tabled critical value at the prespecified level of significance.

Since the obtained value $U = 4$ must be equal to or less than the aforementioned tabled critical values, the null hypothesis can only be rejected if the directional alternative hypothesis $H_1: \theta_1 < \theta_2$ is employed. The directional alternative hypothesis $H_1: \theta_1 < \theta_2$ is supported at the .05 level, since $U = 4$ is equal to the tabled critical one-tailed value $U_{.05} = 4$. The data are consistent with the directional alternative hypothesis $H_1: \theta_1 < \theta_2$, since the average of the ranks in Group 1 is less than the average of the ranks in Group 2 (i.e., $\bar{R}_1 < \bar{R}_2$).³ The directional alternative hypothesis $H_1: \theta_1 < \theta_2$ is not supported at the .01 level, since the obtained value $U = 4$ is greater than the tabled critical one-tailed value $U_{.01} = 1$.

The nondirectional alternative hypothesis $H_1: \theta_1 \neq \theta_2$ is not supported, since the obtained value $U = 4$ is greater than the tabled critical two-tailed value $U_{.05} = 2$.

Since the data are not consistent with the directional alternative hypothesis $H_1: \theta_1 > \theta_2$, the latter alternative hypothesis is not supported. In order for the directional alternative hypothesis $H_1: \theta_1 > \theta_2$ to be supported, the average of the ranks in Group 1 must be greater than the average of the ranks in Group 2 (i.e., $\bar{R}_1 > \bar{R}_2$) (as well as the fact that the computed value of U must be equal to or less than the tabled critical one-tailed value at the prespecified level of significance).

The results of the **Mann–Whitney U test** are consistent with those obtained when the **t test for independent samples** is employed to evaluate Example 11.1 (which employs the same set of data as Example 12.1). In both instances, the null hypothesis can only be rejected if the researcher employs a directional alternative hypothesis that predicts a lower degree of depression in the group that receives the antidepressant medication (Group 1).

VI. Additional Analytical Procedures for the Mann–Whitney U Test and/or Related Tests

1. The normal approximation of the Mann–Whitney U statistic for large sample sizes If the sample size employed in a study is relatively large, the normal distribution can be employed to approximate the **Mann–Whitney U statistic**. Although sources do not agree on the value of the sample size that justifies employing the normal approximation of the Mann–Whitney distribution, they generally state that it should be employed for sample sizes larger than those documented in the exact table of the U distribution contained within the source. Equation 12.4 provides the normal approximation of the **Mann–Whitney U test** statistic.

$$z = \frac{U - \frac{n_1 n_2}{2}}{\sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12}}} \quad \text{(Equation 12.4)}$$

In the numerator of Equation 12.4 the term $(n_1 n_2)/2$ is often summarized with the notation U_E , which represents the expected (mean) value of U if the null hypothesis is true. In other words, if in fact the two groups are equivalent, it is expected that $\bar{R}_1 = \bar{R}_2$. If the latter is true then $U_1 = U_2$, and both of the values U_1 and U_2 will equal $(n_1 n_2)/2$. The denominator in Equation 12.4 represents the expected standard deviation of the sampling distribution for the normal approximation of the U statistic.

Although Example 12.1 involves only $N = 10$ scores (a value most sources would view as too small to use with the normal approximation), it will be employed to illustrate Equation 12.4. The reader will see that in spite of employing Equation 12.4 with a small sample size, it yields a result that is consistent with the result obtained when the exact table for the **Mann–Whitney U** distribution is employed. It should be noted that since the smaller of the two values U_1 versus U_2 is selected to represent U , the value of z will always be negative (unless $U_1 = U_2$, in which case $z = 0$). This is the case, since by selecting the smaller value U will always be less than the expected value $U_E = (n_1 n_2)/2$.

Employing Equation 12.4, the value $z = -1.78$ is computed.⁴

$$z = \frac{4 - \frac{(5)(5)}{2}}{\sqrt{\frac{(5)(5)(5 + 5 + 1)}{12}}} = -1.78$$

The obtained value $z = -1.78$ is evaluated with **Table A1 (Table of the Normal Distribution)** in the **Appendix**. In order to be significant, the obtained absolute value of z must be equal to or greater than the tabled critical value at the prespecified level of significance. The tabled critical two-tailed .05 and .01 values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed .05 and .01 values are $z_{.05} = 1.65$ and $z_{.01} = 2.33$. The following guidelines are employed in evaluating the null hypothesis.

a) If the nondirectional alternative hypothesis $H_1: \theta_1 \neq \theta_2$ is employed, the null hypothesis can be rejected if the obtained absolute value of z is equal to or greater than the tabled critical two-tailed value at the prespecified level of significance.

b) If a directional alternative hypothesis is employed, one of the two possible directional alternative hypotheses is supported if the obtained absolute value of z is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance. The directional alternative hypothesis that is supported is the one that is consistent with the data.

Employing the above guidelines with Example 12.1, the following conclusions are reached.

Since the obtained absolute value $z = 1.78$ must be equal to or greater than the tabled critical value at the prespecified level of significance, the null hypothesis can only be rejected if the directional alternative hypothesis $H_1: \theta_1 < \theta_2$ is employed. The directional alternative hypothesis $H_1: \theta_1 < \theta_2$ is supported at the .05 level, since the absolute value $z = 1.78$ is greater than the tabled critical one-tailed value $z_{.05} = 1.65$. As noted in Section V, the data are consistent with the directional alternative hypothesis $H_1: \theta_1 < \theta_2$. The directional alternative hypothesis $H_1: \theta_1 < \theta_2$ is not supported at the .01 level, since the obtained absolute value $z = 1.78$ is less than the tabled critical one-tailed value $z_{.01} = 2.33$.

The nondirectional alternative hypothesis $H_1: \theta_1 \neq \theta_2$ is not supported, since the obtained absolute value $z = 1.78$ is less than the tabled critical two-tailed .05 value $z_{.05} = 1.96$.

Since the data are not consistent with the directional alternative hypothesis $H_1: \theta_1 > \theta_2$, the latter alternative hypothesis is not supported. As noted in Section V, in order for the latter directional alternative hypothesis to be supported, the following condition must be met: $\bar{R}_1 > \bar{R}_2$.

It turns out that the above conclusions based on the normal approximation are identical to those reached when the exact table of the **Mann–Whitney U distribution** is employed.

It should be noted that, in actuality, either U_1 or U_2 can be employed in Equation 12.4 to represent the value of U . This is the case, since either value yields the same absolute value for z . Thus, if for Example 12.1 $U_1 = 21$ is employed in Equation 12.4, the value $z = 1.78$ is computed. Since the decision with respect to the status of the null hypothesis is a function of the

absolute value of z , the value $z = 1.78$ leads to the same conclusions that are reached when $z = -1.78$ is employed. The decision with regard to a directional alternative hypothesis is not affected, since the data are still consistent with the directional alternative hypothesis $H_1: \theta_1 < \theta_2$.

2. The correction for continuity for the normal approximation of the Mann–Whitney U test⁵ Although not used in most sources, Siegel and Castellan (1988) employ a correction for continuity for the normal approximation of the **Mann–Whitney test** statistic. Marascuilo and McSweeney (1977) note that the correction for continuity is generally not employed, unless the computed absolute value of z is close to the prespecified tabled critical value. The correction for continuity, which reduces the absolute value of z , requires that .5 be subtracted from the absolute value of the numerator of Equation 12.4 (as well as the absolute value of the numerator of the alternative equation described in Endnote 4). The continuity-corrected version of Equation 12.4 is provided by Equation 12.5.

$$z = \frac{\left| U - \frac{n_1 n_2}{2} \right| - .5}{\sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12}}} \quad (\text{Equation 12.5})$$

If the correction for continuity is employed with Example 12.1, the value computed for the numerator of Equation 12.5 is 8 (in contrast to the value 8.5 computed with Equation 12.4). Employing Equation 12.5 with Example 12.1, the value $z = -1.67$ is computed.

$$z = \frac{\left| 4 - \frac{(5)(5)}{2} \right| - .5}{\sqrt{\frac{(5)(5)(5 + 5 + 1)}{12}}} = -1.67$$

Since the absolute value $z = 1.67$ is greater than the tabled critical one-tailed value $z_{.05} = 1.65$, the directional alternative hypothesis $H_1: \theta_1 < \theta_2$ is still supported at the .05 level.

3. Tie correction for the normal approximation of the Mann–Whitney U statistic Some sources recommend that when an excessive number of ties are present in the data, a tie correction should be introduced into Equation 12.4. Equation 12.6 is the tie-corrected equation for the normal approximation of the **Mann–Whitney U distribution**. The latter equation results in a slight increase in the absolute value of z .⁶

$$z = \frac{U - \frac{n_1 n_2}{2}}{\sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12} - \frac{n_1 n_2 \left[\sum_{i=1}^s (t_i^3 - t_i) \right]}{12(n_1 + n_2)(n_1 + n_2 - 1)}}} \quad (\text{Equation 12.6})$$

The only difference between Equations 12.4 and 12.6 is the term to the right of the element $[n_1 n_2 (n_1 + n_2 + 1)]/12$ in the denominator. The result of this subtraction reduces the value of

the denominator, thereby resulting in the slight increase in the absolute value of z . The term $\sum_{i=1}^s (t_i^3 - t_i)$ in the denominator of Equation 12.6 computes a value based on the number of ties in the data. In Example 12.1 there are $s = 2$ sets of ties. Specifically, there is a set of ties involving two subjects with the score 0, and a set of ties involving three subjects with the score 11. The notation $\sum_{i=1}^s (t_i^3 - t_i)$ indicates the following: a) For each set of ties, the number of ties in the set is subtracted from the cube of the number of ties in that set; and b) The sum of all the values computed in part a) is obtained. Thus, for Example 12.1:

$$\sum_{i=1}^s (t_i^3 - t_i) = [(2)^3 - 2] + [(3)^3 - 3] = 30$$

The tie-corrected value $z = -1.80$ is now computed employing Equation 12.6.

$$z = \frac{4 - \frac{(5)(5)}{2}}{\sqrt{\frac{(5)(5)(5 + 5 + 1)}{12} - \frac{(5)(5)(30)}{12(5 + 5)(5 + 5 - 1)}}} = -1.80$$

The difference between $z = -1.80$ and the uncorrected value $z = -1.78$ is trivial, and consequently the decision the researcher makes with respect to the null hypothesis is not affected, regardless of which alternative hypothesis is employed.⁷

4. Sources for computing a confidence interval for the Mann–Whitney U test Various books that specialize in nonparametric statistics (e.g., Daniel (1990) and Marascuilo and McSweeney (1977)) describe the computational procedure for computing a confidence interval that can be used in conjunction with the **Mann–Whitney U test**. The confidence interval identifies a range of values that the true difference between the two population medians is likely to fall.

VII. Additional Discussion of the Mann–Whitney U Test

1. Power-efficiency of the Mann–Whitney U test When the underlying population distributions are normal, the **asymptotic relative efficiency** (which is discussed in Section VII of the **Wilcoxon signed-ranks test (Test 6)**) of the **Mann–Whitney U test** is .955 (when contrasted with the **t test for two independent samples**). For population distributions that are not normal, the asymptotic relative efficiency of the **Mann–Whitney U test** is generally equal to or greater than 1. As a general rule, proponents of nonparametric tests take the position that when a researcher has reason to believe that the normality assumption of the **t test for two independent samples** has been saliently violated, the **Mann–Whitney U test** provides a powerful test of the comparable alternative hypothesis.

2. Equivalency of the normal approximation of the Mann–Whitney U test and the t test for two independent samples with rank-orders Conover (1980, 1999), Conover and Iman (1981), and Zimmerman and Zumbo (1993) note that the large sample normal approximation of the **Mann–Whitney U test** (i.e., Equation 12.4) yields a result that is equivalent (with respect to the exact alpha level computed for the data) to that which will be obtained if the **t test for two independent samples** is conducted on the same set of rank-orders. Even if the normal approximation is not employed, the results obtained from the **Mann–Whitney U test** through use of Equations 12.1 and 12.2 will be extremely close (in terms of the alpha value) to those that

will be obtained if the ***t* test for two independent samples** is conducted on the same set of rank-orders.

3. Alternative nonparametric rank-order procedures for evaluating a design involving two independent samples In addition to the **Mann–Whitney *U* test** a number of other nonparametric procedures for two independent samples have been developed that can be employed with ordinal data. Among the more commonly cited alternative procedures are the following: a) **The Kolmogorov–Smirnov test for two independent samples (Test 13)** (Kolmogorov (1933) and Smirnov (1939)), which is described in the next chapter; b) **The van der Waerden normal-scores test for *k* independent samples (Test 23)** (Van der Waerden (1953/1953)), which is described later in the book, as well as alternative **normal-scores tests** developed by Terry and Hoeffding (Terry (1952)) and Bell and Doksum (1965); c) **Tukey’s quick test** (Tukey (1959)); d) **The median test for independent samples (Test 16e)**, which involves dichotomizing two samples with respect to their median values, and evaluating the data with the **chi-square test for *r* × *c* tables (Test 16)**; e) **The Wald–Wolfowitz runs test** (Wald and Wolfowitz (1940)) (briefly discussed under the **single-sample runs test (Test 10)** within the framework of Example 10.6); and f) **Wilks’ empty-cell test for identical populations** (Wilks (1961)). In addition to various books which specialize in nonparametric statistics, Sheskin (1984) describes these tests in greater detail.

VIII. Additional Examples Illustrating the Use of the Mann–Whitney *U* Test

The **Mann–Whitney *U* test** can be employed with any of the additional examples noted for the ***t* test for two independent samples**. Since Examples 11.4 and 11.5 use the same data as that employed in Example 12.1, they will yield the identical result. Examples 11.2 and 11.3 can also be evaluated with the **Mann–Whitney *U* test**, but employ different data than Example 12.1. The interval/ratio scores in all of the aforementioned examples have to be rank-ordered in order to employ the **Mann–Whitney *U* test**.

Example 12.2 provides one additional example that can be evaluated with the **Mann–Whitney *U* test**. It differs from Example 12.1 in the following respects: a) The original scores are in a rank-order format. Thus, there is no need to transform the scores into ranks from an interval/ratio format (as is the case in Example 12.1). It should be noted though, that it is implied in Example 12.2 that the ranks are based on an underlying interval/ratio scale; and b) The sample sizes are unequal, with $n_1 = 6$ and $n_2 = 7$.

Example 12.2 *Doctor Radical, a math instructor at Logarithm University, has two classes in advanced calculus. There are six students in Class 1 and seven students in Class 2. The instructor uses a programmed textbook in Class 1 and a conventional textbook in Class 2. At the end of the semester, in order to determine if the type of text employed influences student performance, Dr. Radical has another math instructor, Dr. Root, rank the 13 students in the two classes with respect to math ability. The rankings of the students in the two classes follow: Class 1: 1, 3, 5, 7, 11, 13; Class 2: 2, 4, 6, 8, 9, 10, 12 (assume the lower the rank the better the student).*

Employing the **Mann–Whitney *U* test** with Example 12.2 the following values are computed.

$$\Sigma R_1 = 40 \qquad \Sigma R_2 = 51$$

$$U_1 = (6)(7) + \frac{6(6 + 1)}{2} - 40 = 23$$

$$U_2 = (6)(7) + \frac{7(7 + 1)}{2} - 51 = 19$$

$$(U_1 = 23) + (U_2 = 19) = (n_1 = 6)(n_2 = 7) = 42$$

$$z = \frac{19 - \frac{(6)(7)}{2}}{\sqrt{\frac{(6)(7)(6 + 7 + 1)}{12}}} = -.29$$

Since the value $U_2 = 19$ is less than $U_1 = 23$, $U = 19$. Employing [Table A11](#), for $n_1 = 6$ and $n_2 = 7$, the tabled critical two-tailed values are $U_{.05} = 6$ and $U_{.01} = 3$, and the tabled critical one-tailed values are $U_{.05} = 8$ and $U_{.01} = 4$. Since in order to be significant the obtained value $U = 19$ must be equal to or less than the tabled critical value, the null hypothesis $H_0: \theta_1 = \theta_2$ cannot be rejected regardless of which alternative hypothesis is employed. The use of Equation 12.4 for the normal approximation confirms this result, since the absolute value $z = .29$ is less than the tabled critical two-tailed values $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed values $z_{.05} = 1.65$ and $z_{.01} = 2.33$.

IX. Addendum

Computer-intensive tests⁸ During the past 20 years the availability of computers has allowed for the use of hypothesis testing procedures which involve such an excessive amount of computation that in most instances it would be impractical to conduct such tests by hand or even with a conventional calculator. The first statisticians who discussed such tests were Fisher (1935) and Pitman (1937a, 1937b, 1938), who described procedures known as **randomization** or **permutation tests**. Aside from their computer friendliness, another reason for the increased popularity of the **computer-intensive procedures** (also referred to as **data-driven procedures** (Sprent, 1998)) to be discussed in this section is that they have associated with them few if any of the distributional assumptions that underlie parametric tests, as well as certain nonparametric tests. As it is employed in this book, the term **computer-intensive test/procedure** is used to describe any of a variety of procedures that are computer dependent.⁹

The computer dependency of such tests reflects the fact that in addition to carrying out numerous computations, many of these tests employ the computer as a mechanism for repeated **resampling** of data. Julian Simon (1969) was among those who first discussed the advantages of employing computer based resampling in the analysis of data. Resampling is a process in which subsets of scores are selected from an original set of data. In the final analysis, the distinguishing feature between the various computer-intensive procedures that employ resampling is the specific protocol employed in selecting subsamples from the original set of data. Two resampling procedures that will be described in the **Addendum** are the **bootstrap** (developed by Efron (Efron (1979) and Efron and Tibshirani (1993)) and the **jackknife** (developed by Quenouille (1949) and named by Tukey (1958)).¹⁰ The intent of the discussion to follow is to present the reader with the basic principles underlying computer-intensive procedures. Those who are interested in a more in-depth discussion of this complex topic should consult sources such as Manly (1997) and Sprent (1998), or other relevant references that are cited in this **Addendum**.

Randomization and permutations tests The terms **permutation test**, **randomization test**, **rerandomization test**, and **exact test** are employed interchangeably by many sources (Good, (1994)). Within the context of such tests, the word **permutation** is used to represent a specific configuration/arrangement of scores. Such tests yield results that are exclusively a function of the observed data, and are not based on any assumptions regarding an underlying population distribution. The use of the term **randomization test** reflects the fact that in most instances such tests contrast two or more groups to which it is assumed subjects have been randomly assigned. Although the data such tests are employed to evaluate need not be a random sample, if random selection cannot be assumed, it will limit the generalizability of the test's results. Randomization tests evaluate the data obtained in an experiment within the framework of the distribution of all possible random arrangements that can be obtained for that set of data. In a randomization test, instead of evaluating the outcome of an experiment in reference to some underlying theoretical population distribution (e.g., the normal, t , F distributions, etc.), the data itself are employed to construct the relevant sampling distribution. By constructing a sampling distribution based on the data, the researcher is not restricted by any assumptions which might be associated with an underlying theoretical distribution. The fact that it is a requirement of a randomization test to compute a separate sampling distribution is the reason why, in almost all instances, a computer is needed to conduct such a test. In this section the principles underlying randomization tests will be demonstrated in reference to evaluating an experiment involving two independent samples. In the example presented, a randomization test will be employed to do the following: a) Evaluate the interval/ratio scores of two independent groups; and b) Evaluate the rank-orderings of the same set of interval/ratio scores. In the case of the latter analysis, it will be demonstrated that it is equivalent to the analysis conducted for the **Mann–Whitney U test** with the same set of ranks. This is the case since the **Mann–Whitney U test** (as well as many other rank-order tests) represents an example of a randomization/permutation test that is based upon permutations of ranks (i.e., configurations/arrangements of ranks).

Test 12a: The randomization test for two independent samples Among the other names that are employed for the test to be described in this section are **Fisher's randomization test for two independent samples** and the **Fisher–Pitman test** (since the procedure was first described by Fisher (1935) and Pitman (1937a, 1937b, 1938)). If a researcher has serious doubts regarding the normality and/or homogeneity of variance assumptions underlying the **t test for two independent samples**, the **randomization test for two independent samples** provides one with a viable alternative for evaluating the data. The data will be represented by the interval/ratio scores of two independent samples with n_1 scores in Group 1 and n_2 scores in Group 2, with $n_1 + n_2 = N$. Example 12.3 will be employed to illustrate the use of the **randomization test for two independent samples**.¹¹

Example 12.3 *Each of six subjects is randomly assigned to one of two groups, with $n_1 = 3$ subjects in Group 1 and $n_2 = 3$ subjects in Group 2. While attempting to solve a mechanical problem, the subjects in Group 1 are exposed to a high concentration of atmospheric ozone. The subjects in Group 2 are required to solve the same mechanical problem under normal atmospheric conditions. The number of minutes it takes each of the subjects in the two groups to solve the problem follows: **Group 1:** 15, 18, 21; **Group 2:** 7, 10, 11. Do the data indicate that there are differences between the two groups?*

The null and alternative hypotheses evaluated with the **randomization test for two independent samples** are stated below. Note that, as stated, the null and alternative hypotheses

do not include any reference to a population parameter. If a researcher included a population parameter in H_0 and H_1 , there would be certain assumptions about the underlying population that would have to be met.

Null hypothesis H_0 : There is no difference in the performance of the two groups. If the null hypothesis is supported, one can conclude that the two groups represent the same population.

Alternative hypothesis H_1 : The performance of the two groups is not equivalent. If the alternative hypothesis is supported, one can conclude that the two groups do not represent the same population.

The alternative hypothesis stated above is **nondirectional**, and is evaluated with a **two-tailed test**. Either of the **directional alternative hypotheses** noted below can also be employed. If a **directional alternative hypothesis** is employed, a **one-tailed test** is conducted.

Alternative hypothesis H_1 : The scores of subjects in Group 1 are higher than the scores of subjects in Group 2.

Alternative hypothesis H_1 : The scores of subjects in Group 1 are lower than the scores of subjects in Group 2.

The general question that is addressed by the **randomization test for two independent samples** is as follows: If the scores of all N subjects are collapsed into a single group, how likely is it that the specific configuration of scores obtained in the experiment will be obtained if we randomly select n_1 scores and assigned them to Group 1 and assign the remaining $N - n_1 = n_2$ scores to Group 2? Common sense suggests that if chance is operating, we will expect an equivalent distribution of scores in the two groups. On the other hand, if there are differences between the groups, it is expected that the distributions will not be equivalent. Thus, if one group has a preponderance of high scores and the other group has a preponderance of low scores, we will want to determine the exact likelihood of obtaining such an outcome purely as a result of chance. By constructing a sampling distribution from the data, the **randomization test for two independent samples** allows us to do this.

In order to evaluate the data for Example 12.3, we must first answer the following question: How many ways can six subjects can be assigned to two groups with three subjects per group? This is equivalent to asking, what are the number of combinations of six things taken three at a time? (The reader may find it useful to review the discussion of **combinations** in Section IV of the **binomial sign test for a single sample (Test 9)**.) Employing Equation 9.4, we determine that the number of combinations of six things taken three at a time is equal to 20: $\binom{6}{3} = \frac{6!}{3! 3!} = 20$. This result tells us that there are 20 possible ways that six subjects can be assigned to two groups with three subjects per group.¹²

Table 12.3 summarizes the 20 possible ways in which the six scores 7, 10, 11, 15, 18, and 21 can be distributed between two groups with $n_1 = 3$ and $n_2 = 3$. The left side of Table 12.3 (Columns 2 and 3) lists the 20 possible ways three scores can be randomly assigned to Group 1 (or Group 2), as well as the sum of the three scores for each arrangement. The last two columns of the table are based on the assumption that the six scores have been converted into ranks, and lists the rank-orders for the three interval/ratio scores in a given row (Column 4), and the sum of the rank-orders for that row (Column 5). Within the framework of the 20 arrangements that are listed, Column 4 contains each of the possible ways three rank-orderings within a set of six rank-orderings can be randomly assigned to Group 1 (or Group 2).¹³

Table 12.3 Possible Arrangements for Example 12.3 Data

Arrangement	Scores in Group 1	Sum of Scores in Group 1	Ranks in Group 1	Sum of Ranks in Group 1
1	7, 10, 11	28	1, 2, 3	6
2	7, 10, 15	32	1, 2, 4	7
3	7, 11, 15	33	1, 3, 4	8
4	7, 10, 18	35	1, 2, 5	8
5	7, 11, 18	36	1, 3, 5	9
6	10, 11, 15	36	2, 3, 4	9
7	7, 10, 21	38	1, 2, 6	9
8	7, 11, 21	39	1, 3, 6	10
9	10, 11, 18	39	2, 3, 5	10
10	7, 15, 18	40	1, 4, 5	10
11	10, 11, 21	42	2, 3, 6	11
12	7, 15, 21	43	1, 4, 6	11
13	10, 15, 18	43	2, 4, 5	11
14	11, 15, 18	44	3, 4, 5	12
15	10, 15, 21	46	2, 4, 6	12
16	7, 18, 21	46	1, 5, 6	12
17	11, 15, 21	47	3, 4, 6	13
18	10, 18, 21	49	2, 5, 6	13
19	11, 18, 21	50	3, 5, 6	14
20	15, 18, 21	54	4, 5, 6	15

Table 12.4 Sampling Distribution for Sums of Scores in Example 12.3

Sum of Scores	Frequency	Probability	Cumulative Probability
28	1	.05	.05
32	1	.05	.10
33	1	.05	.15
35	1	.05	.20
36	2	.10	.30
38	1	.05	.35
39	2	.10	.45
40	1	.05	.50
42	1	.05	.55
43	2	.10	.65
44	1	.05	.70
46	2	.10	.80
47	1	.05	.85
49	1	.05	.90
50	1	.05	.95
54	1	.05	1.00
Sums	20	1.00	

The values that are computed for the sums of the three interval/ratio scores for each of the 20 arrangements will represent the points on the abscissa (*X*-axis) of the sampling distribution we will employ to evaluate the data. Since some of the 20 arrangements yield the same sum, there are a total of 16 possible values the sum of three scores can assume. The frequency or likelihood of occurrence for each of the 16 sums will be represented on the ordinate (*Y*-axis). [Table 12.4](#) summarizes the probabilities for the 16 sums of scores. Note that in [Table 12.4](#) the sums of the scores are arranged in increasing order of magnitude, and that the sum of the column labelled **Frequency** is equal to 20, which is the total number of arrangements for the interval/ratio scores

for our data. The probability distribution in Columns 3 and 4 of [Table 12.4](#) represents the sampling distribution that is employed within the framework of the **randomization test for two independent samples** to evaluate the null hypothesis. Column 3 lists the probability for the sum of scores in each row, whereas Column 4 lists the cumulative probability for the sum of scores in that row (cumulative probabilities are discussed in the **Kolmogorov–Smirnov goodness-of-fit test for a single sample (Test 7)**).

[Table 12.5](#) summarizes the sampling distribution for the sums of ranks. It turns out that for our data there are only 10 possible values the sum of three ranks can equal. The frequency or likelihood of occurrence for each of the 10 sums of ranks is summarized in [Table 12.5](#). Note that in [Table 12.5](#) the sums of the ranks are arranged in increasing order of magnitude, and that the sum of Column 2 (labelled **Frequency**) is equal to 20, which is the total number of arrangements of ranks for our data. The probability distribution in [Table 12.5](#) (Column 3 lists the probability for the sum of ranks in each row, whereas Column 4 lists the cumulative probability for the sum of ranks in that row) represents the sampling distribution that can be employed within the framework of the **randomization test for two independent samples** to evaluate the null hypothesis. It should be emphasized, however, that the original test developed by Fisher (1935) and Pitman (1937a, 1937b, 1938) evaluated the sums of interval/ratio scores and not summed values that were based on ranks. Thus, when summed values based on the ranks of two independent samples are evaluated using the **Fisher–Pitman randomization procedure**, the test is not generally referred to as the **randomization test for two independent samples**. Instead it is referred to as the **Mann–Whitney *U* test**.¹⁴

Table 12.5 Sampling Distribution for Sums of Ranks in Example 12.3

Sum of Ranks	Frequency	Probability	Cumulative Probability
6	1	.05	.05
7	1	.05	.10
8	2	.10	.20
9	3	.15	.35
10	3	.15	.50
11	3	.15	.65
12	3	.15	.80
13	2	.10	.90
14	1	.05	.95
15	1	.05	1.00
Sums	20	1.00	

In order to reject the null hypothesis, the sum of scores/ranks (and consequently the arrangement which yields a specific sum) will have to be one that is highly unlikely to occur as a result of chance. In the case of a **two-tailed alternative hypothesis** this will translate into an arrangement with a sum of scores/ranks that is either very high or very low. In the case of a **one-tailed alternative hypothesis**, the following will apply: a) In order for the **one-tailed alternative hypothesis** predicting that the scores of the subjects in Group 1 are higher than the scores of the subjects in Group 2 to be supported, it will require an arrangement where the sum of scores/ranks for Group 1 is very high; b) In order for the **one-tailed alternative hypothesis** predicting that the scores of the subjects in Group 1 are lower than the scores of the subjects in Group 2 to be supported, it will require an arrangement where the sum of scores/ranks for Group 1 is very low.

In point of fact, the sum of scores for the observed data in Group 1 is 54 (based on the three scores 15, 18, and 21), which is the largest possible sum in [Tables 12.3](#) and [12.4](#). In the same respect, the sum of the ranks for the observed ranks in Group 1 is 15 (based on the ranks 4, 5, and

6 for the three scores 15, 18, and 21), which is the largest possible sum of ranks in [Tables 12.3](#) and [12.5](#). In both instances the likelihood of obtaining a sum of that magnitude is .05 (or 5%).¹⁵ The latter value delineates the upper 5% of the sampling distribution we have derived for the data. This result allows us to reject the null hypothesis at the .05 level, but only for the **one-tailed alternative hypothesis** predicting that the scores of the subjects in Group 1 are higher than the scores of the subjects in Group 2. The latter alternative hypothesis is supported since there is only a 5% likelihood that a sum of scores or ranks equal to or greater than the one observed could have occurred as a result of chance.

The null hypothesis cannot be rejected if the **one-tailed alternative hypothesis** predicting that the scores of the subjects in Group 1 are lower than the scores of the subjects in Group 2 is employed. This is the case, since the data are inconsistent with the latter alternative hypothesis.

The null hypothesis cannot be rejected at the .05 level if the **two-tailed alternative hypothesis** is employed. The reason for this is that even though the observed data results in the highest possible sum of scores/ranks, the total number of possible arrangements is 20. As a result of the latter, the lowest probability possible for the most extreme arrangement in either direction (the highest or lowest sum) is $1/20 = .05$. In order for a **two-tailed alternative hypothesis** to be supported, it will require that the observed data fall within the extreme 5% of the cases involving both tails of the distribution. One-half of that 5% will have to come from the upper tail of the sampling distribution, and the other half from the lower tail. Thus, in order for the two-tailed alternative hypothesis to be supported, it will require that the probability associated with the highest sum (as well as the lowest sum) be equal to or less than $.05/2 = .025$. In our example, the small sample size (which results in 20 arrangements) does not allow us to evaluate a two-tailed alternative hypothesis at the .05 level, since it is not possible for the highest sum (or lowest sum) to have a probability as low as .025. In order to evaluate the two-tailed alternative hypothesis at that level, there would have to be a minimum of 40 arrangements (since $1/40 = .025$). It should be evident that because of our small sample size, it is not possible to evaluate the one-tailed or two-tailed alternative hypotheses at the .01 level.

It was noted earlier in the discussion of randomization tests that the **Mann–Whitney *U* test** represents an example of a randomization test that is based upon permutations of ranks (i.e., configurations/arrangements of ranks). What this translates into is that, if the data for Example 12.3 are evaluated with the **Mann–Whitney *U* test**, it should yield a result identical to that obtained with the **randomization test for two independent samples**, when the latter procedure is applied to ranks. This will now be demonstrated by evaluating the data for Example 12.3 with the **Mann–Whitney *U* test**.

From [Table 12.3](#) we know that the sum of the ranks for Group 1 is $\sum R_1 = 15$ (which is the sum of the ranks 4, 5, and 6 for the three scores 15, 18, and 21). Since the three scores for Group 2 are the three lowest scores, the sum of the ranks for Group 2 will equal $\sum R_2 = 6$ (which is the sum of the ranks 1, 2, and 3 for the three scores 7, 10, and 11). Employing Equations 12.1 and 12.2, we obtain $U_1 = 0$ and $U_2 = 9$.

$$U_1 = (3)(3) + \frac{3(3 + 1)}{2} - 15 = 0$$

$$U_2 = (3)(3) + \frac{3(3 + 1)}{2} - 6 = 9$$

Since the smaller of the two values U_1 versus U_2 is designated as the U statistic, $U = 0$. Note that in [Table A11](#) no tabled critical two-tailed .05 U value is listed for $n_1 = 3$ and $n_2 = 3$. The tabled critical one-tailed .05 value listed for $n_1 = 3$ and $n_2 = 3$ is $U_{.05} = 0$. No tabled

critical .01 U values are listed due to the small samples size. Since the obtained value $U = 0$ is equal to the tabled critical one-tailed .05 value $U_{.05} = 0$, the one-tailed alternative hypothesis predicting that the scores of the subjects in Group 1 are higher than the scores of the subjects in Group 2 is supported at the .05 level. The one-tailed alternative hypothesis predicting that the scores of the subjects in Group 1 are lower than the scores of the subjects in Group 2 is not supported, since it is inconsistent with the observed data. Because no critical two-tailed values are listed in **Table A11** for $n_1 = 3$ and $n_2 = 3$, the two-tailed alternative hypothesis cannot be evaluated at the .05 level. The results of the **Mann–Whitney U test** are thus identical to those obtained when the data for Example 12.3 are evaluated with the **randomization test for two independent samples** (in which case the one-tailed alternative hypothesis that is consistent with the data is supported at the .05 level).

When the size of the samples for which a randomization test is employed becomes large, the number of possible combinations that can be computed for the data may become excessive to the point that it even becomes impractical for a computer to construct an exact sampling distribution based on every possible arrangement. In such a situation an **approximate randomization test** may be used. In the latter test, the computer constructs a sampling distribution based on randomly selecting a large number (but not all) of the possible arrangements for the data. The resulting sampling distribution is employed to evaluate the sample data.

Good (1994, p. 114) notes that under certain conditions a randomization test may provide a more powerful test of an alternative hypothesis than a parametric procedure. Sprent (1998, p. 52), however, points out a limitation of the **randomization test for two independent samples** is that if the test is employed with interval/ratio data containing one or more **outliers**, it behaves very much like the **t test for two independent samples** (and thus may be unreliable). Conover (1999, p. 408) notes that when the **randomization test for two independent samples** is applied to interval/ratio data, under certain conditions (e.g., outliers present in the data, skewed distributions) it provides a less powerful test of an alternative hypothesis than an analogous parametric procedure or a nonparametric rank-order procedure (which as noted in this section may be a randomization test on rank-orders). Lundbrook and Dudley (1998) provide a good history of randomization tests, and discuss the merits of employing such tests in biomedical research. Manly (1997) provides a comprehensive discussion of randomization tests.

Test 12b: The bootstrap Sprent (1998, p. 28) notes that although the philosophy underlying the bootstrap is different from that upon which permutation tests are based, it employs a similar methodology, and often yields results that are concordant with those which will be obtained with a permutation test. The bootstrap is based on the general assumption that a random sample can be used to determine the characteristics of the underlying population from which the sample is derived. However, instead of the using a sample statistic (e.g., the sample standard deviation) to estimate a population parameter (e.g., the population standard deviation), as is done within the framework of conventional parametric statistical tests, the bootstrap uses multiple samples derived from the original data to provide what in some instances may be a more accurate measure of the population parameter.¹⁶ The most common application of the bootstrap involves estimating a population standard error and/or confidence interval.

The more ambiguous the information available to a researcher regarding an underlying population distribution, the more likely it is that the bootstrap may prove useful. Sprent (1998) notes that unlike permutation tests, which are able to provide a researcher with exact probability values, the use of the bootstrap only leads to approximate results. Nevertheless, in this case approximate results may, in the final analysis, be considerably more accurate than the results derived from an analysis that is based on an invalid theoretical model. For this reason, proponents of the bootstrap justify its use in circumstances where there is reasonable doubt regarding the

characteristics of the underlying population distribution from which a sample is drawn. The most frequent justification for using the bootstrap is when there is reason to believe that data may not be derived from a normally distributed population.¹⁷ Another condition that might merit the use of the bootstrap is one involving a sample that contains one or more **outliers** (outliers are discussed in Section VII of the ***t* test for two independent samples**). If, as a result of outliers being present in the data, a researcher elects to trim scores from the tails of a sample distribution, there is no equation available for providing the researcher with an unbiased estimate of certain population parameters (e.g., the standard error).

Efron and Tibshirani (1993, p. 393) note that the bootstrap implements familiar statistical calculations (e.g., computing standard errors, confidence intervals, etc.) in an unfamiliar way — specifically, through use of computer driven methods, as opposed to the use of mathematical equations. They state that, even though it employs a different methodology, the bootstrap is based on mathematical theory which insures its compatibility with traditional theories of statistical inference. Sprent (1993, p. 291) notes that bootstrapping can be a valuable technique when there is no clear analytic theory to obtain a measure of accuracy of an estimator. According to Efron and Tibshirani (1993, p. 394), at present the accuracy of the bootstrap is optimal in the estimation of values such as standard errors and confidence intervals, and it is weakest in evaluating those hypotheses which are typically evaluated with the more conventional inferential statistical tests.

At this point the methodology for the bootstrap will be demonstrated with a simple example. It is assumed that within the framework of actual research, the procedure to be described below would be carried out with a computer. Additionally, the sample size employed in a study will generally be larger than the value $n = 5$ employed in the example. Obviously, if a sample is randomly drawn for a population, the larger the value of n (i.e., the sample size) the more likely it is that the sample will be representative of the population. It is important to note that as a result of chance factors, even a random sample can be unrepresentative of an underlying population. To the degree that a sample is not representative of a population, the bootstrap will not provide an accurate estimate of the parameter under investigation. The general issue of what size a sample should be in order to employ the bootstrap is subject to debate. Mooney and Duval (1993) note that in most instances a random sample comprised of 30-50 observations will be sufficient to provide a good bootstrap estimate. Although Manly (1997) states that the theory underlying the bootstrap insures that it will work well in certain situations involving large samples, he notes that in actuality a substantial amount of published research does not employ large samples. Under such circumstances Manly (1997) states that the use of the bootstrap becomes more problematical. To illustrate the latter, he provides an example involving data derived from an exponential distribution which requires a sample size of more than 100 in order for the bootstrap to provide an accurate estimate of a confidence interval.¹⁸

An example will now be presented to illustrate the application of the bootstrap methodology in computing a confidence interval.

Example 12.4 *Assume that five diamonds are randomly selected from a population of diamonds manufactured by one of the world's largest distributor of precious stones. For each of the $n = 5$ diamonds, the number of imperfections observed on its surface is recorded. Let us assume there is reason to believe that the distribution of imperfections in the underlying population of diamonds is not normal. The number of imperfections observed in each of the five diamonds that comprise our sample follows: 12, 7, 8, 2, 4. A quality control supervisor in the company requests a 99% confidence interval for the population standard deviation for the number of imperfections per diamond. Employ the bootstrap to compute a 99% confidence interval for the population standard deviation. (For a full discussion of **confidence intervals** the reader should review the appropriate material in Section VI of the **single-sample *t* test (Test 2)**.)*

The methodology of the bootstrap requires that **sampling with replacement** be employed to select a large number of subsamples from the sample of five scores (Endnote 1 of the **binomial sign test for a single sample (Test 9)** explains the distinction between **sampling with replacement** versus **sampling without replacement**). We will let m represent the number of subsamples. Each of the m subsamples will be referred to as a **bootstrap sample**. As is the case with our original sample, the sample size for each of the bootstrap samples will be $n = 5$. Since we will employ sampling with replacement, within any bootstrap sample any of the original five scores can occur any number of times ranging from zero to five (since within any bootstrap sample, each score selected will always be randomly drawn from the pool of five scores that constitute the original sample). Let us assume we obtain $m = 1000$ bootstrap samples (all of which are randomly generated by a computer algorithm that selects random samples through use of sampling with replacement). The scores for the first two and last of the 1000 bootstrap samples are noted below.

Bootstrap sample 1: 2, 2, 7, 8, 12

Bootstrap sample 2: 8, 12, 7, 7, 12

.....

Bootstrap sample 1000: 2, 4, 12, 8, 12

Employing Equation I.8, the computer calculates the unbiased estimate of the standard deviation for each of the $m = 1000$ bootstrap samples. The computation of \tilde{s} is demonstrated for **Bootstrap sample 1** (where $\sum X_1 = 31$ and $\sum X_1^2 = 265$).

$$\tilde{s}_1 = \sqrt{[265 - [(31)^2/5]]/(5 - 1)} = 4.27$$

The computed values of \tilde{s} for **Bootstrap sample 2** and **Bootstrap sample 1000** are $\tilde{s}_2 = 2.59$ and $\tilde{s}_{1000} = 4.56$. Once we have computed the standard deviation values for all 1000 bootstrap samples, the values are arranged ordinally — i.e., from lowest to highest. At this point we can employ the 1000 \tilde{s} values to determine the 99% confidence interval. The 99% confidence interval stipulates the range of values within which we can be 99% confident the population standard deviation falls (or stated probabilistically, there is a .99 probability the population standard deviation falls within the confidence interval). One-half of one per cent (.5% or .005 expressed as a proportion) of the scores fall to the left of the lower bound of the 99% confidence interval, and one-half of one per cent (.5%) of the scores fall to the right of the upper bound of the 99% confidence interval. The scores in between the two bounds fall within the 99% confidence interval. Thus, in the case of our $m = 1000$ bootstrap sample standard deviations, the middle 99% will fall within the 99% confidence interval. The extreme .5% in the left tail (i.e., the .5% lowest \tilde{s} values computed) and the extreme .5% in the right tail (i.e., the .5% highest \tilde{s} values computed) will fall outside the 99% confidence interval. Thus, the lower bound of the 99% confidence interval will be the score at the sixth ordinal position. We obtain the value of the latter ordinal position by multiplying $m = 1000$ (the total number of scores in our sampling distribution of standard deviation scores) by .005 (i.e., 5%) and adding 1 (i.e., $m(.005) + 1 = (1000)(.005) + 1 = 6$). Five of the 1000 scores will fall below that point. The upper bound of the 99% confidence interval will be the score in the 995th ordinal position. We obtain the latter ordinal position value by multiplying $m = 1000$ by .005, and subtracting the resultant value of 5 from 1000 (i.e., $m - m(.005) = 1000 - (1000)(.005) = 995$). Five of the 1000 scores will fall above that point. Assume that of the total 1000 bootstrap standard deviations computed, the six lowest and six highest values are listed below.

0 0 .45 .45 .89 .89 4.27 4.47 4.47 4.47 4.67 4.67

Since the sixth score from the bottom is .89 and the sixth score from the top (which corresponds ordinarily to the 995th score) is 4.27, the latter values represent the bounds that define the 99% confidence interval. Thus, we can conclude that we can be 99% confident (or the probability is .99) that the true value of the population standard deviation falls within the range .89 and 4.27. This result can be summarized as follows: $.89 \leq \sigma \leq 4.27$.

It should be emphasized that the use of the bootstrap in Example 12.4 for computing a confidence interval will be predicated on the fact that the researcher is unaware of any acceptable mathematical method for accurately determining the confidence interval. Efron and Tibshirani (1993, p. 52) note that while estimating a standard error rarely necessitates more than 200 bootstrap samples, the computation of a confidence interval generally requires a minimum of 1000 bootstraps, and often considerably more depending upon the nature of the problem being evaluated (see Efron and Tibshirani (1993, Ch. 12–14) for a more detailed discussion).

The bootstrap can be applied to numerous hypothesis testing situations. As an example, Efron and Tibshirani (1993) and Sprent (1998) discuss the use of the bootstrap in evaluating the null hypothesis that two samples are derived from the same population. One approach to the two-sample hypothesis testing situation is to use the bootstrap in a manner analogous to that employed for a permutation test. However, instead of employing sampling without replacement, as is the case with a permutation test (since for each arrangement, n_1 scores are placed in one group, and the remaining $N - n_1 = n_2$ scores by default constitute the other group), sampling with replacement is employed for the bootstrap. To illustrate, assume that we have two samples comprised of n_1 subjects in Group 1 and n_2 subjects in Group 2, with $n_1 + n_2 = N$. Using the total of N scores, employing sampling with replacement, we employ the computer to randomly select a large number of bootstrap samples, each sample being comprised of N scores. Within each bootstrap sample, the first n_1 scores are employed to represent the scores for Group 1 and the remaining $N - n_1 = n_2$ scores are employed to represent the scores for Group 2. For each bootstrap sample, a difference score between the two group means is computed. The empirical sampling distribution of the difference scores is employed to evaluate the null hypothesis. Specifically, it is determined how likely it is to have obtained the observed difference in the original data when it is considered within the framework of a large number of bootstrap sample difference scores. This is essentially what is done in a permutation test, and Efron and Tibshirani (1993, p. 221) note that when a large number of bootstrap samples (e.g., 1000) are employed, the bootstrap and permutation test applied to the same set of data yield similar results. However, Efron and Tibshirani (1993, p. 220) make the general statement that although bootstrap tests are more widely applicable than permutation tests within the framework of hypothesis testing situations, they are not as accurate. As noted earlier in this section, the bootstrap is more accurate in estimating values such as standard errors and confidence intervals than it is in the area of hypothesis testing.

In concluding this discussion, it should be emphasized that the bootstrap is a relatively new methodology. Consequently, at the present time, the method itself is the subject of considerable research which focuses on both its theoretical underpinnings and practical applications. Manly (1997) notes that although the bootstrap is based on a very simple concept, over the years the theory behind it has become increasingly complex. (Many of the applications of the bootstrap, as well as the theory behind them, are considerably more involved than what has been discussed in this section.) One could conjecture that if a researcher does not understand the theory or operations underlying a statistical procedure, one may become increasingly reluctant to use it, or, because of one's ignorance, use it inappropriately. Manly (1997) recommends that in the future, appropriate user-friendly applications of the bootstrap be integrated into standard statistical software.

Test 12c: The jackknife Another computer-intensive procedure that was developed (by Quenouille (1949)) prior to the bootstrap is the **jackknife**. Like the bootstrap, the jackknife is an alternative methodology available to the researcher that can be employed for point/interval estimation. Specifically, under certain conditions the jackknife can be employed to reduce the degree of bias associated with point estimation (i.e., increase accuracy in estimating a population parameter). Like the bootstrap, the jackknife might be considered as a viable alternative in situations where there is no clear analytic theory to obtain a measure of accuracy of an estimator. At this point a simple example will be presented to demonstrate how the jackknife can be employed to estimate the degree of bias associated with an estimator of a parameter. The data for Example 12.4 will be employed to demonstrate the use of the jackknife in estimating bias in the following situations: a) Employing \bar{X} , the sample mean (which is known to be an unbiased estimator of the population mean (μ)), to estimate the value of the population mean; and b) Employing the sample variance (s^2) as computed with Equation I.4 (which is known to be a biased estimator of the population variance (σ^2)) to estimate the value of the population variance.

Employing Equation I.1, we compute the sample mean for the data of Example 12.4 (i.e., the $n=5$ scores 12, 7, 8, 2, 4) to be $\bar{X} = 6.6$. Employing Equation I.4, the sample variance (s^2), which is known to be a biased estimate of σ^2 , is computed to be $s^2 = 11.84$ ($s^2 = [277 - [(33)^2/5]]/5 = 11.84$). Employing Equation I.5, the estimated population variance (\hat{s}^2), which is known to be an unbiased estimate of σ^2 , is computed to be $\hat{s}^2 = 14.8$ ($\hat{s}^2 = [277 - [(33)^2/5]]/4 = 14.8$).

The methodology of the jackknife requires that n subsamples, to be designated **jackknife samples**, be derived from the original sample of n scores. Each of the jackknife samples will be comprised of $(n - 1)$ scores. In each of the n jackknife samples one of the original n scores is omitted. From the original set of 5 scores 12, 7, 8, 2, 4, we can derive the following five jackknife samples, comprised of four scores per sample: **Jackknife sample 1:** 7, 8, 2, 4; **Jackknife sample 2:** 12, 8, 2, 4; **Jackknife sample 3:** 12, 7, 2, 4; **Jackknife sample 4:** 12, 7, 8, 4; **Jackknife sample 5:** 12, 7, 8, 2. Note that in **Jackknife sample 1** the first of the five scores listed is omitted, and in **Jackknife sample 2** the second of the five scores listed is omitted, and so on. Thus, each of the samples is comprised of four of the original five scores.

Employing Equations I.1 and I.4 we compute the mean (\bar{X}) and sample variance (s^2) for each of the five jackknife samples. These values are summarized below.

$$\begin{aligned}\bar{X}_1 &= 5.25 & \bar{X}_2 &= 6.5 & \bar{X}_3 &= 6.25 & \bar{X}_4 &= 7.75 & \bar{X}_5 &= 7.25 \\ s_1^2 &= 5.6875 & s_2^2 &= 14.75 & s_3^2 &= 14.1875 & s_4^2 &= 8.1875 & s_5^2 &= 12.6875\end{aligned}$$

Sprent (1993, p. 285) notes that Equation 12.7 is the general equation for computing a **jackknife estimate of a specific parameter θ** (where θ is the lower case Greek letter **theta**). Equation 12.8 is the general equation for the **jackknife estimate of the degree of bias** associated with the estimate, which will be represented with value B .

$$\theta_j = n\theta' - (n - 1)\theta_* \quad \text{(Equation 12.7)}$$

Where: θ_j represents the jackknife estimate of the parameter
 θ' represents the value of the statistic computed for the parameter from the original sample data comprised of n scores
 θ_* represents the average value of the sample statistic computed for the n jackknife samples. (The same statistic employed to compute θ' should be employed to compute the estimate of the parameter for the n jackknife samples.)

$$B = (n - 1)(\theta_* - \theta') \quad (\text{Equation 12.8})$$

In employing the jackknife estimator of the population mean (μ), the symbol θ will be used to represent the population mean. The following values will be employed in Equations 12.7 and 12.8: a) $n = 5$; b) $\theta' = \bar{X} = 6.6$, since that is the mean value of the five scores 12, 7, 8, 2, 4; and c) $\theta_* = 6.6$, since that is the mean of five jackknife samples (i.e., $(5.25 + 6.5 + 6.25 + 7.75 + 7.25)/5 = 6.6$). The appropriate values are substituted in Equations 12.7 and 12.8.

$$\theta_j = 5(6.6) - (5 - 1)(6.6) = 6.6$$

$$B = (5 - 1)(6.6 - 6.6) = 0$$

The computed value $\theta_j = 6.6$ is the jackknife estimate of the population mean. The computed value $B = 0$ indicates that the degree of bias associated with the sample statistic \bar{X} in estimating the population mean is zero. Since in the case of the population mean it is known that \bar{X} provides an unbiased estimate of μ , it is expected that the value zero will be computed for B .

In employing the jackknife estimator of the population variance (σ^2), the symbol θ will be used to represent the population variance. The following values will be employed in Equations 12.7 and 12.8: a) $n = 5$; b) $\theta' = s^2 = 11.84$, since that is the value computed with Equation 1.4 for the sample variance for the five scores 12, 7, 8, 2, 4; and c) $\theta_* = 11.1$, since that is the mean of the variances of the five jackknife samples (i.e., $(5.6875 + 14.75 + 14.1875 + 8.1875 + 12.6875)/5 = 11.1$). The appropriate values are substituted in Equations 12.7 and 12.8.

$$\theta_j = 5(11.84) - (5 - 1)(11.1) = 14.8$$

$$B = (5 - 1)(11.1 - 11.84) = -2.96$$

The computed value $\theta_j = 14.8$ is the jackknife estimate of the population variance. The computed value $B = -2.96$ indicates that the degree of bias associated with the sample statistic s^2 in estimating the population variance is -2.96 (the negative sign indicating underestimation of the population variance by 2.96 units through use of the sample statistic s^2). Note that the computed value $\theta_j = 14.8$ is 2.96 units above the value $s^2 = 11.84$, and that $\theta_j = 14.8$, is, in fact, equivalent to the unbiased estimate of the population variance $\hat{\sigma}^2 = 14.8$ computed with Equation 1.5. In point of fact, if the value $\hat{\sigma}^2 = 14.8$ is employed in Equations 12.7 and 12.8, to represent θ' , Equation 1.5 is employed to compute the five jackknife variances (and the average of the five jackknife $\hat{\sigma}^2$ values is $\theta_* = 14.8$). In such a case, the jackknife estimate of the variance computed with Equation 12.7 remains unchanged, yielding the value $\theta_j = 14.8$. However, the resulting value computed with Equation 12.8 will equal zero, since, as is the case when \bar{X} is employed to estimate μ , $\hat{\sigma}^2 = 14.8$ is an unbiased estimate of the population variance.

Sprent (1993, 1998) and Efron and Tibshirani (1993, p. 148) note that the jackknife will be ineffective in reducing bias for some parameters. As an example, both of the aforementioned authors demonstrate the ineffectiveness of the jackknife as an estimator of the population median. These authors, as well as Hollander and Wolfe (1999) discuss a modified jackknife procedure referred to as the **delete- d jackknife**. In the latter modification of the standard jackknife, d scores are omitted from each of the jackknife samples, where d is some integer value greater than 1. Under certain conditions the latter procedure may provide a more accurate estimate of a population parameter than use of the conventional jackknife where $d = 1$. The reader should take note of the fact that for a set of n scores, the number of jackknife samples will be limited in number and be a function of the value of n , while the number of bootstrap samples that can be

employed for a set of n scores is unlimited. Within this context, Efron and Tibshirani (1993) note that since the jackknife employs less data than the bootstrap, it is less efficient, and in the final analysis, what the jackknife provides is an approximation of the results obtained with the bootstrap. Manly (1997) and Mooney and Duval (1993) (both of whom present detailed discussions of the jackknife and the bootstrap) describe analytical situations in which they state or demonstrate that the jackknife provides more accurate information than the bootstrap.

Final comments on computer-intensive procedures Procedures such as the bootstrap and jackknife are commonly discussed in books that address the general subject of **robust statistical procedures** (e.g., Huber (1981), Sprent (1993, 1998), Staudte and Sheather (1990)) — the latter term referring to statistical procedures which are not overly dependent on critical assumptions regarding an underlying population distribution (the concept of robustness is discussed in Section VII of the ***t* test for two independent samples**). Conover (1999, p. 116) notes that the term **robustness** is most commonly applied to methods that are employed when the normality assumption underlying an inferential statistical test is violated. He points out that in spite of the fact that when sample sizes are reasonably large certain tests such as the **single-sample *t* test** and the ***t* test for two independent samples** are known to be robust with respect to violation of the normality assumption (i.e., the accuracy of the tabled critical alpha values for the test statistics are not compromised), if the underlying distribution is not normal, the power of such tests may still be appreciably reduced. Related to this is the fact that Staudte and Sheather (1990, p. 14) paint a bleak picture regarding the power of commonly employed **goodness-of-fit tests for normality**. Specifically, these authors suggest that unless a sample size is relatively large, goodness-of-fit tests for normality (such as the **Kolmogorov–Smirnov goodness-of-fit test for a single sample** or the **chi-square goodness-of-fit test (Test 8)**) will generally not result in rejection of the null hypothesis of normality, unless the fit with respect to normality is dramatically violated. Consequently, they conclude that most goodness-of-fit tests are ineffective mechanisms for providing confirmation for the normal distribution assumption that more often than not researchers assume characterizes an underlying population. Staudte and Sheather (1990) argue that as a result of the failure of goodness-of-fit tests to reject the normal distribution model, procedures based on the assumption of normality all too often are employed with data that are derived from nonnormal populations. In instances where the normality assumption is violated, Staudte and Sheather (1990) encourage a researcher to consider employing a **robust statistical procedure** (such as the bootstrap) to analyze the data. In accordance with this view, Sprent (1998) notes that the bootstrap will often yield a more accurate result for a nonnormal population than will analysis of the data with a statistical test which assumes normality.

Another characteristic of data that is often discussed within the framework of robust statistical procedures is the subject of **outliers** alluded to earlier in this section (for a more comprehensive discussion of outliers, the reader should consult Section VII of the ***t* test for two independent samples**). Research has shown that a single outlier can substantially compromise the power of a parametric statistical test. (Staudte and Sheather (1990) provide an excellent example of this involving the **single-sample *t* test**.) Various sources suggest that when one or more outliers are present in a set of data, a computer-intensive procedure (such as the bootstrap or jackknife) may provide a researcher with more accurate information regarding the underlying population(s) than a parametric procedure.

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Endnotes

1. The test to be described in this chapter is also referred to as the **Wilcoxon rank-sum test** and the **Mann–Whitney–Wilcoxon test**.
2. The reader should take note of the following with respect to the table of critical values for the **Mann–Whitney U distribution**: a) No critical values are recorded in the **Mann–Whitney table** for very small sample sizes, since a level of significance of .05 or less cannot be achieved for sample sizes below a specific minimum value; b) The critical values published in **Mann–Whitney tables** by various sources may not be identical. Such differences are trivial (usually one unit), and are the result of rounding off protocol; and c) The table for the alternative version of the **Mann–Whitney U test** (which was developed by Wilcoxon (1949)) contains critical values that are based on the sampling distribution of the sums of ranks, which differ from the tabled critical values contained in **Table A11** (which represents the sampling distribution of U values).
3. Although for Example 12.1 we can also say that since $\sum R_1 < \sum R_2$ the data are consistent with the directional alternative hypothesis $H_1: \theta_1 < \theta_2$, the latter will not necessarily

always be the case when $n_1 \neq n_2$. Since the relationship between the average of the ranks will always be applicable to both equal and unequal sample sizes, it will be employed in describing the hypothesized relationship between the ranks of the two groups.

4. Some sources employ an alternative normal approximation equation which yields the same result as Equation 12.4. The alternative equation is noted below.

$$z = \frac{\sum R_1 - n_1 \left[\frac{n_1 + n_2 + 1}{2} \right]}{\sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12}}}$$

Note that the only difference between the above equation and Equation 12.4 is with respect to the numerator. If the value $\sum R_1 = 19$ from Example 12.1 is substituted in the above equation, it yields the value -8.5 for the numerator (which is the value for the numerator computed with Equation 12.4), and consequently the value $z = -1.78$. If $\sum R_2$ is employed in the numerator of the above equation in lieu of $\sum R_1$, the numerator of the equation assumes the form $\sum R_2 - [n_2(n_1 + n_2 + 1)]/2$. If $\sum R_2 = 36$ is substituted in the revised numerator, the value 8.5 is computed for the numerator, which results in the value $z = 1.78$. (Later on in this discussion it will be noted that the same conclusions regarding the null hypothesis are reached with the values $z = 1.78$ and $z = -1.78$.) The above equation is generally employed in sources that describe the version of the **Mann-Whitney U test** developed by Wilcoxon (1949). The latter version of the test only requires that the sum of the ranks be computed for each group, and does not require the computation of U values. As noted in Endnote 1, the table of critical values for the alternative version of the test is based on the sampling distribution of the sums of the ranks.

5. A general discussion of the correction for continuity can be found under the **Wilcoxon signed-ranks test**.
6. Some sources employ the term below for the denominator of Equation 12.6. It yields the identical result.

$$\sigma_U = \sqrt{\frac{n_1 n_2}{N(N-1)} \left[\frac{N^3 - N}{12} - \sum_{i=1}^s \frac{(t_i^3 - t_i)}{12} \right]}$$

7. A correction for continuity can be used by subtracting .5 from the value computed in the numerator of the Equation 12.6. The continuity correction will reduce the absolute value of z .
8. The rationale for discussing computer-intensive procedures in the **Addendum** of the **Mann-Whitney U test** is that the **Mann-Whitney test** (as well as many other rank-order procedures) can be conceptualized an example of a **randomization** or **permutation test**, which is the first of the computer based procedures to be described in the **Addendum**.
9. Another application of a computer-intensive procedure is **Monte Carlo research** which is discussed in Section VII of the **single-sample runs test**.

10. The term **bootstrap** is derived from the saying that a person lifts oneself up by one's bootstraps. Within the framework of the statistical procedure, bootstrapping indicates that a single sample is used as a basis for generating multiple additional samples — in other words, one makes the most out of what little resources one has. Manly (1997) notes that the use of the term **jackknife** is based on the idea that a jackknife is a multipurpose tool which can be used for many tasks, in spite of the fact that for any single task it is seldom the best tool.
11. The reader should take note of the fact that although Example 12.3 involves two independent samples, by using the basic methodology to be described in this section, randomization tests can be employed to evaluate virtually any type of experimental design.
12. a) Suppose in the above example we have an unequal number of subjects in each group. Specifically, let us assume two subjects are randomly assigned to Group 1 and four subjects to Group 2. The total number of possible arrangements will be the combination of six things taken two at a time, which is equivalent to the combination of six things taken four at a time. This results in 15 different arrangements: $\binom{6}{2} = \binom{6}{4} = \frac{6!}{2! 4!} = 15$; b) To illustrate how large the total number of arrangements can become, suppose we have a total of 40 subjects and randomly assign 15 subjects to Group 1 and 25 subjects to Group 2. The total number of possible arrangements is the combination of 40 things taken 15 at a time, which is equivalent to the combination of 40 things taken 25 at a time. The total number of possible arrangements will be $\binom{40}{15} = \binom{40}{25} = \frac{40!}{15! 25!} = 40,225,345,060$. Obviously, without the aid of a computer it will be impossible to evaluate such a large number of arrangements.
13. The reader should take note of the following: a) If the 20 corresponding arrangements for Group 2 are listed in [Table 12.3](#), the same 20 arrangements that are listed for Group 1 will appear in the table, but in different rows. To illustrate, the first arrangement in [Table 12.3](#) for Group 1 is comprised of the scores 7, 10, 11. The corresponding Group 2 arrangement is 15, 18, 21 (which are the three remaining scores in the sample). In the last row of [Table 12.3](#) the scores 15, 18, 21 are listed. The corresponding arrangement for Group 2 will be the remaining scores, which are 7, 10, 11. If we continue this process for the remaining 18 Group 1 arrangements, the final distribution of arrangements for Group 2 will be comprised of the same 20 arrangements obtained for Group 1; b) When $n_1 \neq n_2$, the distribution of the arrangements of the scores in the two groups will not be identical, since all the arrangements in Group 1 will always have n_1 scores and all the arrangements in Group 2 will always have n_2 scores, and $n_1 \neq n_2$. Nevertheless, computation of the appropriate sampling distribution for the data only requires that a distribution be computed which is based on the arrangements for one of the two groups. Employing the distribution for the other group will yield the identical result for the analysis.
14. Although the result obtained with the **Mann–Whitney U test** is equivalent to the result that will be obtained with a randomization/permutation test conducted on the rank-orders, only the version of the test that was developed by Wilcoxon (1949) directly evaluates the permutations of the ranks. Marascuilo and McSweeney (1977, pp. 270–272) and Sprent (1998, pp. 85–86) note that the version of the test described by Mann and Whitney (1947) actually employs a statistical model which evaluates the number of **inversions** in the data. An **inversion** is defined as follows: Assume that we begin with the assumption that all the

scores in one group (designated Group 1) are higher than all the scores in the other group (designated Group 2). If we compare all the scores in Group 1 with all the scores in Group 2, an inversion is any instance in which a score in Group 1 is not higher than a score in Group 2. It turns out an inversion based model yields a result that is equivalent to that obtained when the permutations of the ranks are evaluated (as is done in Wilcoxon's (1949) version of the **Mann–Whitney U test**). Employing the data from Example 12.1, consider [Table 12.6](#) where the scores in Group 1 are arranged ordinally in the top row, and the scores in Group 2 are arranged ordinally in the left column.

Table 12.6 Inversion Model of Mann–Whitney U test

		Group 1 Scores				
		0	0	1	2	11
Group 2 Scores	4	–4	–4	–3	–2	7
	5	–5	–5	–4	–3	6
	8	–8	–8	–7	–6	3
	11	–11	–11	–10	–9	0
	11	–11	–11	–10	–9	0

Each of the scores in the cells of [Table 12.6](#) are difference scores that are the result of subtracting the score in the row a cell appears (i.e., the corresponding Group 2 score) from the score at the top of the column in which the cells appears (i.e., the corresponding Group 1 score). Note that any negative difference score recorded in the table meets the criterion established for an **inversion**. Ties result in a zero value for a cell. The total number of inversions in the data is based on the number of negative difference scores and the number of ties. One point is allocated for each negative difference score, and one-half a point for each zero/tie (since the latter is viewed as a less extreme inversion than one associated with a negative difference score). Employing the aforementioned protocol, the number of inversions in the [Table 12.6](#) is the 20 negative difference scores plus the two zeros, which sums to 21 inversions. Note that the latter value corresponds to the value computed for U_1 with Equation 12.1. The value $U_2 = 4$ inversions will be obtained if [Table 12.6](#) is reconstructed so that the score in each column (i.e., Group 1 score) is subtracted from the score in the corresponding row (i.e., Group 2 score).

15. Although in this example the identical probability is obtained for the highest sum of scores and highest sum of ranks, this will not always be the case.
16. Efron and Tibshirani (1993, p. 394) note that the bootstrap differs from more conventional simulation procedures (discussed briefly in Section VII of the **single-sample runs test**), in that in conventional simulation, data are generated through use of a theoretical model (such as sampling from a theoretical population such as a normal distribution for which the mean and standard deviation have been specified). In the bootstrap the simulation is data-based. Specifically, multiple samples are drawn from a sample of data that is derived in an experiment. One problem with the bootstrap is that since it involves drawing random subsamples from a set of data, two or more researchers conducting a bootstrap may not reach the same conclusions due to differences in the random subsamples generated.
17. Sprent (1998) notes that when the bootstrap is employed correctly in situations where the normality assumption is not violated, it generally yields conclusions that will be consistent with those derived from the use of conventional parametric and nonparametric tests, as well as permutation tests.

18. The exponential distribution is a continuous probability distribution which is often useful in investigating reliability theory and stochastic processes. Manly (1997) recommends that prior to employing the bootstrap for inferential purposes, it is essential to evaluate its performance with small samples derived from various theoretical probability distributions (such as the exponential distribution). Monte Carlo studies (i.e., computer simulations involving the derivation of samples from theoretical distributions for which the values of the relevant parameters have been specified) can be employed to evaluate the reliability of the bootstrap.

Test 13

The Kolmogorov–Smirnov Test for Two Independent Samples (Nonparametric Test Employed with Ordinal Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test Do two independent samples represent two different populations?

Relevant background information on test The **Kolmogorov–Smirnov test for two independent samples** was developed by Smirnov (1939). Daniel (1980) notes that because of the similarity between Smirnov’s test and a goodness-of-fit test developed by Kolmogorov (1933) (the **Kolmogorov–Smirnov goodness-of-fit test for a single sample (Test 7)**), the test to be discussed in this chapter is often referred to as the **Kolmogorov–Smirnov test for two independent samples** (although other sources (Conover (1980, 1999)) simply refer to it as the **Smirnov test**).

Daniel (1990), Marascuilo and McSweeney (1977), and Siegel and Castellan (1988) note that when a nondirectional/two-tailed alternative hypothesis is evaluated, the **Kolmogorov–Smirnov test for two independent samples** is sensitive to any kind of distributional difference (i.e., a difference with respect to location/central tendency, dispersion/variability, skewness, and kurtosis). When a directional/one-tailed alternative hypothesis is evaluated, the test evaluates the relative magnitude of the scores in the two distributions.

As is the case with the **Kolmogorov–Smirnov goodness-of-fit test for a single sample** discussed earlier in the book, computation of the test statistic for the **Kolmogorov–Smirnov test for two independent samples** involves the comparison of two **cumulative frequency distributions**. Whereas the **Kolmogorov–Smirnov goodness-of-fit test for a single sample** compares the cumulative frequency distribution of a single sample with a hypothesized theoretical or empirical cumulative frequency distribution, the **Kolmogorov–Smirnov test for two independent samples** compares the cumulative frequency distributions of two independent samples. If, in fact, the two samples are derived from the same population, the two cumulative frequency distributions would be expected to be identical or reasonably close to one another. The test protocol for the **Kolmogorov–Smirnov test for two independent samples** is based on the principle that if there is a significant difference at any point along the two cumulative frequency distributions, the researcher can conclude there is a high likelihood the samples are derived from different populations.

The **Kolmogorov–Smirnov test for two independent samples** is categorized as a test of ordinal data because it requires that cumulative frequency distributions be constructed (which requires that within each distribution scores be arranged in order of magnitude). Further clarification of the defining characteristics of a cumulative frequency distribution can be found in the **Introduction**, and in Section I of the **Kolmogorov–Smirnov goodness-of-fit test for a single sample**. Since the **Kolmogorov–Smirnov test for two independent samples** represents

a nonparametric alternative to the ***t* test for two independent samples (Test 11)**, the most common situation in which a researcher might elect to employ the **Kolmogorov–Smirnov test** to evaluate a hypothesis about two independent samples (where the dependent variable represents interval/ratio measurement) is when there is reason to believe that the normality and/or homogeneity of variance assumption of the ***t* test** have been saliently violated. The **Kolmogorov–Smirnov test for two independent samples** is based on the following assumptions: a) All of the observations in the two samples are randomly selected and independent of one another; and b) The scale of measurement is at least ordinal.

II. Example

Example 13.1 is identical to Examples 11.1/12.1 (which are evaluated with the ***t* test for two independent samples** and the **Mann–Whitney *U* test (Test 12)**).

Example 13.1 *In order to assess the efficacy of a new antidepressant drug, ten clinically depressed patients are randomly assigned to one of two groups. Five patients are assigned to Group 1, which is administered the antidepressant drug for a period of six months. The other five patients are assigned to Group 2, which is administered a placebo during the same six-month period. Assume that prior to introducing the experimental treatments, the experimenter confirmed that the level of depression in the two groups was equal. After six months elapse all ten subjects are rated by a psychiatrist (who is blind with respect to a subject's experimental condition) on their level of depression. The psychiatrist's depression ratings for the five subjects in each group follow (the higher the rating, the more depressed a subject): **Group 1:** 11, 1, 0, 2, 0; **Group 2:** 11, 11, 5, 8, 4. Do the data indicate that the antidepressant drug is effective?*

III. Null versus Alternative Hypotheses

Prior to reading the null and alternative hypotheses to be presented in this section, the reader should be take note of the following: a) The protocol for the **Kolmogorov–Smirnov test for two independent samples** requires that a cumulative probability distribution be constructed for each of the samples. The test statistic is defined by the point that represents the greatest vertical distance at any point between the two cumulative probability distributions; and b) Within the framework of the null and alternative hypotheses, the notation $F_j(X)$ represents the population distribution from which the j^{th} sample/group is derived. $F_j(X)$ can also be conceptualized as representing the cumulative probability distribution for the population from which the j^{th} sample/ group is derived.

Null hypothesis $H_0: F_1(X) = F_2(X)$ for all values of X

(The distribution of data in the population that Sample 1 is derived from is consistent with the distribution of data in the population that Sample 2 is derived from. Another way of stating the null hypothesis is as follows: At no point is the greatest vertical distance between the cumulative probability distribution for Sample 1 (which is assumed to be the best estimate of the cumulative probability distribution of the population from which Sample 1 is derived) and the cumulative probability distribution for Sample 2 (which is assumed to be the best estimate of the cumulative probability distribution of the population from which Sample 2 is derived) larger than what would be expected by chance, if the two samples are derived from the same population distribution.)

Alternative hypothesis $H_1: F_1(X) \neq F_2(X)$ for at least one value of X

(The distribution of data in the population that Sample 1 is derived from is not consistent with the distribution of data in the population that Sample 2 is derived from. Another way of stating this alternative hypothesis is as follows: There is at least one point where the greatest vertical distance between the cumulative probability distribution for Sample 1 (which is assumed to be the best estimate of the cumulative probability distribution of the population from which Sample 1 is derived) and the cumulative probability distribution for Sample 2 (which is assumed to be the best estimate of the cumulative probability distribution of the population from which Sample 2 is derived) is larger than what would be expected by chance, if the two samples are derived from the same population distribution. At the point of maximum deviation separating the two cumulative probability distributions, the cumulative probability for Sample 1 is either significantly greater or less than the cumulative probability for Sample 2. This is a **nondirectional alternative hypothesis** and it is evaluated with a **two-tailed test**.)

or

$H_1: F_1(X) > F_2(X)$ for at least one value of X

(The distribution of data in the population that Sample 1 is derived from is not consistent with the distribution of data in the population that Sample 2 is derived from. Another way of stating this alternative hypothesis is as follows: There is at least one point where the greatest vertical distance between the cumulative probability distribution for Sample 1 (which is assumed to be the best estimate of the cumulative probability distribution of the population from which Sample 1 is derived) and the cumulative probability distribution for Sample 2 (which is assumed to be the best estimate of the cumulative probability distribution of the population from which Sample 2 is derived) is larger than what would be expected by chance, if the two samples are derived from the same population distribution. At the point of maximum deviation separating the two cumulative probability distributions, the cumulative probability for Sample 1 is significantly greater than the cumulative probability for Sample 2. This is a **directional alternative hypothesis** and it is evaluated with a **one-tailed test**.)

or

$H_1: F_1(X) < F_2(X)$ for at least one value of X

(The distribution of data in the population that Sample 1 is derived from is not consistent with the distribution of data in the population that Sample 2 is derived from. Another way of stating this alternative hypothesis is as follows: There is at least one point where the greatest vertical distance between the cumulative probability distribution for Sample 1 (which is assumed to be the best estimate of the cumulative probability distribution of the population from which Sample 1 is derived) and the cumulative probability distribution for Sample 2 (which is assumed to be the best estimate of the cumulative probability distribution of the population from which Sample 2 is derived) is larger than what would be expected by chance, if the two samples are derived from the same population distribution. At the point of maximum deviation separating the two cumulative probability distributions, the cumulative probability for Sample 1 is significantly less than the cumulative probability for Sample 2. This is a **directional alternative hypothesis** and it is evaluated with a **one-tailed test**.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis is rejected.

IV. Test Computations

As noted in Sections I and III, the test protocol for the **Kolmogorov–Smirnov test for two independent samples** contrasts the two sample cumulative probability distributions with one another. [Table 13.1](#) summarizes the steps that are involved in the analysis. There are a total of $n = 10$ scores, with $n_1 = 5$ scores in Group 1 and $n_2 = 5$ scores in Group 2.

Table 13.1 Calculation of Test Statistic for Kolmogorov–Smirnov Test for Two Independent Samples for Example 13.1

A (X_1)	B $S_1(X)$	C (X_2)	D $S_2(X)$	E $S_1(X) - S_2(X)$
0,0	$2/5 = .40$	–	0	$.40 - 0 = .40$
1	$3/5 = .60$	–	0	$.60 - 0 = .60$
2	$4/5 = .80$	–	0	$.80 - 0 = .80$
–	$4/5 = .80$	4	$1/5 = .20$	$.80 - .20 = .60$
–	$4/5 = .80$	5	$2/5 = .40$	$.80 - .40 = .40$
–	$4/5 = .80$	8	$3/5 = .60$	$.80 - .60 = .20$
11	$5/5 = 1.00$	11, 11	$5/5 = 1.00$	$1.00 - 1.00 = .00$

The values represented in the columns of [Table 13.1](#) are summarized below.

The values of the psychiatrist's depression ratings for the subjects in Group 1 are recorded in **Column A**. Note that there are five scores recorded in **Column A**, and that if the same score is assigned to more than one subject in Group 1, each of the scores of that value are recorded in the same row in **Column A**.

Each value in **Column B** represents the cumulative proportion associated with the value of the X score recorded in **Column A**. The notation $S_1(X)$ is commonly employed to represent the cumulative proportions for Group/Sample 1 recorded in **Column B**. The value in **Column B** for any row is obtained as follows: a) The Group 1 cumulative frequency for the score in that row (i.e., the frequency of occurrence of all scores in Group 1 equal to or less than the score in that row) is divided by the total number of scores in Group 1 ($n_1 = 5$). To illustrate, in the case of **Row 1**, the score 0 is recorded twice in **Column A**. Thus, the cumulative frequency is equal to 2, since there are 2 scores in Group 1 that are equal to 0 (a depression rating score cannot be less than 0). Thus, the cumulative frequency 2 is divided by $n_1 = 5$, yielding $2/5 = .40$. The value .40 in **Column B** represents the cumulative proportion in Group 1 associated with a score of 0. It means that the proportion of scores in Group 1 that is equal to 0 is .40. The proportion of scores in Group 1 that is larger than 0 is .60 (since $1 - .40 = .60$). In the case of **Row 2**, the score 1 is recorded in **Column A**. The cumulative frequency is equal to 3, since there are 3 scores in Group 1 that are equal to or less than 1 (2 scores of 0 and a score of 1). Thus, the cumulative frequency 3 is divided by $n_1 = 5$, yielding $3/5 = .60$. The value .60 in **Column B** represents the cumulative proportion in Group 1 associated with a score of 1. It means that the proportion of scores in Group 1 that is equal to or less than 1 is .60. The proportion of scores in Group 1 that is larger than 1 is .40 (since $1 - .60 = .40$). In the case of **Row 3**, the score 2 is recorded in **Column A**. The cumulative frequency is equal to 4, since there are 4 scores in Group 1 that are equal to or less than 2 (two scores of 0, a score of 1, and a score of 2). Thus, the cumulative frequency 4 is divided by $n_1 = 5$, yielding $4/5 = .80$. The value .80 in **Column B** represents the cumulative proportion in Group 1 associated with a score of 2. It means that the proportion of scores in Group 1 that is equal to or less than 2 is .80. The proportion of scores in Group 1 that is larger than 2 is .20 (since $1 - .80 = .20$). Note that the value of the cumulative proportion in **Column B** remains .8 in **Rows 4, 5, and 6**, since until a new score is recorded in **Column A**, the cumulative proportion recorded in **Column B** will remain the same. In the case of **Row 7**, the

score 11 is recorded in **Column A**. The cumulative frequency is equal to 5, since there are 5 scores in Group 1 that are equal to or less than 11 (i.e., all of the scores in Group 1 are equal to or less than 11). Thus, the cumulative frequency 5 is divided by $n_1 = 5$, yielding $5/5 = 1$. The value 1 in **Column B** represents the cumulative proportion in Group 1 associated with a score of 11. It means that the proportion of scores in Group 1 that is equal to or less than 11 is 1. The proportion of scores in Group 1 that is larger than 11 is 0 (since $1 - 1 = 0$).

The values of the psychiatrist's depression ratings for the subjects in Group 2 are recorded in **Column C**. Note that there are five scores recorded in **Column C**, and if the same score is assigned to more than one subject in Group 2, each of the scores of that value are recorded in the same row in **Column C**.

Each value in **Column D** represents the cumulative proportion associated with the value of the X score recorded in **Column C**. The notation $S_2(X)$ is commonly employed to represent the cumulative proportions for Group/Sample 2 recorded in **Column D**. The value in **Column D** for any row is obtained as follows: a) The Group 2 cumulative frequency for the score in that row (i.e., the frequency of occurrence of all scores in Group 2 equal to or less than the score in that row) is divided by the total number of scores in Group 2 ($n_2 = 5$). To illustrate, in the case of **Rows 1, 2, and 3**, no score is recorded in **Column C**. Thus, the cumulative frequencies for each of those rows is equal to 0, since up to that point in the analysis there are no scores recorded for Group 2. Consequently, for each of the first three rows, the cumulative frequency 0 is divided by $n_2 = 5$, yielding $0/5 = 0$. In each of the first three rows, the value 0 in **Column D** represents the cumulative proportion for Group 2 up to that point in the analysis. For each of those rows, the proportion of scores in Group 2 that remain to be analyzed is 1 (since $1 - 0 = 1$). In the case of **Row 4**, the score 4 is recorded in **Column C**. The cumulative frequency is equal to 1, since there is 1 score in Group 2 that is equal to or less than 4 (i.e., the score 4 in that row). Thus, the cumulative frequency 1 is divided by $n_2 = 5$, yielding $1/5 = .20$. The value .20 in **Column D** represents the cumulative proportion in Group 2 associated with a score of 4. It means that the proportion of scores in Group 2 that is equal to or less than 4 is .20. The proportion of scores in Group 2 that is larger than 4 is .80 (since $1 - .20 = .80$). In the case of **Row 5**, the score 5 is recorded in **Column C**. The cumulative frequency is equal to 2, since there are 2 scores in Group 2 that are equal to or less than 5 (the scores of 4 and 5). Thus, the cumulative frequency 2 is divided by $n_2 = 5$, yielding $2/5 = .40$. The value .40 in **Column D** represents the cumulative proportion in Group 2 associated with a score of 5. It means that the proportion of scores in Group 2 that is equal to or less than 5 is .40. The proportion of scores in Group 2 that is larger than 5 is .60 (since $1 - .40 = .60$). In the case of **Row 6**, the score 8 is recorded in **Column C**. The cumulative frequency is equal to 3, since there are 3 scores in Group 2 that are equal to or less than 8 (the scores of 4, 5, and 8). Thus, the cumulative frequency 3 is divided by $n_2 = 5$, yielding $3/5 = .60$. The value .60 in **Column D** represents the cumulative proportion in Group 2 associated with a score of 8. It means that the proportion of scores in Group 2 that is equal to or less than 8 is .60. The proportion of scores in Group 2 that is larger than 8 is .40 (since $1 - .60 = .40$). In the case of **Row 7**, the score 11 is recorded twice in **Column C**. The cumulative frequency is equal to 5, since there are 5 scores in Group 2 that are equal to or less than 11 (i.e., all of the scores in Group 2 are equal to or less than 11). Thus, the cumulative frequency 5 is divided by $n_2 = 5$, yielding $5/5 = 1$. The value 1 in **Column D** represents the cumulative proportion in Group 2 associated with a score of 11. It means that the proportion of scores in Group 2 that is equal to or less than 11 is 1. The proportion of scores in Group 2 that is larger than 11 is 0 (since $1 - 1 = 0$).

The values in **Column E** are difference scores between the cumulative proportions recorded in **Row B** for Group 1 and **Row D** for Group 2. Thus, for **Row 1** the entry in **Column E** is .40, which represents the **Column B** cumulative proportion of .40 for Group 1, minus 0, which

represents the **Column D** cumulative proportion for Group 2. For **Row 2** the entry in **Column E** is .60, which represents the **Column B** cumulative proportion of .60 for Group 1, minus 0, which represents the **Column D** cumulative proportion for Group 2. The same procedure is employed with the remaining five rows in the table.

As noted in Section III, the test statistic for the **Kolmogorov–Smirnov test for two independent samples** is defined by the greatest vertical distance at any point between the two cumulative probability distributions. The largest absolute value obtained in **Column E** will represent the latter value. The notation M will be employed for the test statistic. In [Table 13.1](#) the largest absolute value is .80 (which is recorded in **Row 3**). Therefore, $M = .80$.¹

V. Interpretation of the Test Results

The test statistic for the **Kolmogorov–Smirnov test for two independent samples** is evaluated with [Table A23](#) (**Table of Critical Values for the Kolmogorov–Smirnov test for two independent samples**) in the **Appendix**. If, at any point along the two cumulative probability distributions, the greatest distance (i.e., the value of M) is equal to or greater than the tabled critical value recorded in [Table A23](#), the null hypothesis is rejected. The critical values in [Table A23](#) are listed in reference to the values of n_1 and n_2 . For $n_1 = 5$ and $n_2 = 5$, the tabled critical two-tailed .05 and .01 values in are $M_{.05} = .800$ and $M_{.01} = .800$, and the tabled critical one-tailed .05 and .01 values are $M_{.05} = .600$ and $M_{.01} = .800$.²

The following guidelines are employed in evaluating the null hypothesis for the **Kolmogorov–Smirnov test for two independent samples**.

a) If the nondirectional alternative hypothesis $H_1: F_1(X) \neq F_2(X)$ is employed, the null hypothesis can be rejected if the computed value of the test statistic is equal to or greater than the tabled critical two-tailed M value at the prespecified level of significance.

b) If the directional alternative hypothesis $H_1: F_1(X) > F_2(X)$ is employed, the null hypothesis can be rejected if the computed value of the test statistic is equal to or greater than the tabled critical one-tailed M value at the prespecified level of significance. Additionally, the difference between the two cumulative probability distributions must be such that in reference to the point that represents the test statistic, the cumulative probability for Sample 1 must be larger than the cumulative probability for Sample 2.

c) If the directional alternative hypothesis $H_1: F_1(X) < F_2(X)$ is employed, the null hypothesis can be rejected if the computed value of the test statistic is equal to or greater than the tabled critical one-tailed M value at the prespecified level of significance. Additionally, the difference between the two cumulative probability distributions must be such that in reference to the point that represents the test statistic, the cumulative probability for Sample 1 must be less than the cumulative probability for Sample 2.

The above guidelines will now be employed in reference to the computed test statistic $M = .80$.

a) If the nondirectional alternative hypothesis $H_1: F_1(X) \neq F_2(X)$ is employed, the null hypothesis can be rejected at both the .05 and .01 levels, since $M = .80$ is equal to the tabled critical two-tailed values $M_{.05} = .800$ and $M_{.01} = .800$.

b) If the directional alternative hypothesis $H_1: F_1(X) > F_2(X)$ is employed, the null hypothesis can be rejected at both the .05 and .01 levels, since $M = .80$ is greater than or equal to the tabled critical one-tailed values $M_{.05} = .600$ and $M_{.01} = .800$. Additionally, since in **Row 3** of [Table 13.1](#) [$S_1(X) = .80$] > [$S_2(X) = 0$], the data are consistent with the alternative hypothesis $H_1: F_1(X) > F_2(X)$. In other words, for the computed value of M , the cumulative proportion for Sample 1 is larger than the cumulative proportion for Sample 2.

c) If the directional alternative hypothesis $H_1: F_1(X) < F_2(X)$ is employed, the null

hypothesis cannot be rejected, since in order for the latter alternative hypothesis to be supported, for the computed value of M , the cumulative proportion for Sample 2 must be larger than the cumulative proportion for Sample 1 (which is not the case in **Row 3** of [Table 13.1](#)).

A summary of the analysis of Example 13.1 with the **Kolmogorov–Smirnov test for two independent samples** follows: It can be concluded that there is a high likelihood the two groups are derived from different populations. More specifically, the data indicate that the depression ratings for Group 1 (i.e., the group that receives the antidepressant medication) are significantly less than the depression ratings for Group 2 (the placebo group).

When the same set of data is evaluated with the **t test for two independent samples** and the **Mann–Whitney U test** (i.e., Examples 11.1/12.1), in the case of both of the latter tests, the null hypothesis can only be rejected (and only at the .05 level) if the researcher employs a directional alternative hypothesis that predicts a lower level of depression for Group 1. The latter result is consistent with the result obtained with the **Kolmogorov–Smirnov test**, in that the directional alternative hypothesis $H_1: F_1(X) > F_2(X)$ is supported. Note, however, that the latter directional alternative hypothesis is supported at both the .05 and .01 levels when the **Kolmogorov–Smirnov test** is employed. In addition, the nondirectional alternative hypothesis is supported at both the .05 and .01 levels with the **Kolmogorov–Smirnov test**, but is not supported when the **t test** and **Mann–Whitney U test** are used. Although the results obtained with the **Kolmogorov–Smirnov test for two independent samples** are not identical with the results obtained with the **t test for two independent samples** and the **Mann–Whitney U test**, they are reasonably consistent.

It should be noted that in most instances the **Kolmogorov–Smirnov test for two independent samples** and the **t test for two independent samples** are employed to evaluate the same set of data, the **Kolmogorov–Smirnov test** will provide a less powerful test of an alternative hypothesis. Thus, although it did not turn out to be the case for Examples 11.1/13.1, if a significant difference is present, the **t test** will be the more likely of the two tests to detect it. Siegel and Castellan (1988) note that when compared with the **t test for two independent samples**, the **Kolmogorov–Smirnov test** has a power efficiency (which is defined in Section VII of the **Wilcoxon signed-ranks test (Test 6)**) of .95 for small sample sizes, and a slightly lower power efficiency for larger sample sizes.

VI. Additional Analytical Procedures for the Kolmogorov–Smirnov Test for Two Independent Samples

1. Graphical method for computing the Kolmogorov–Smirnov test statistic Conover (1980, 1999) employs a graphical method for computing the **Kolmogorov–Smirnov test** statistic that is based on the same logic as the graphical method that is briefly discussed for computing the test statistic for the **Kolmogorov–Smirnov goodness-of-fit test for a single sample**. The method involves constructing a graph of the cumulative probability distribution for each sample and measuring the point of maximum distance between the two cumulative probability distributions. Daniel (1990) describes a graphical method that employs a graph referred to as a **pair chart** as an alternative way of computing the **Kolmogorov–Smirnov test** statistic. The latter method is attributed to Hodges (1958) and Quade (1973) (who cites Drion (1952) as having developed the pair chart).

2. Computing sample confidence intervals for the Kolmogorov–Smirnov test for two independent samples The same procedure that is described for computing a confidence interval for cumulative probabilities for the sample distribution that is evaluated with the **Kolmogorov–Smirnov goodness-of-fit test for a single sample** can be employed to compute a confidence interval for cumulative probabilities for either one of the samples that are evaluated with the

Kolmogorov–Smirnov test for two independent samples. Specifically, Equation 7.1 is employed to compute the upper and lower limits for each of the points in a confidence interval. Thus, for each sample, $M_{\alpha/2}$ is added to and subtracted from each of the $S_j(X)$ values. Note that the value of $M_{\alpha/2}$ employed in constructing a confidence interval for each of the samples is derived from [Table A21 \(Table of Critical Values for the Kolmogorov–Smirnov Goodness-of-Fit Test for a Single Sample\)](#) in the **Appendix**. Thus, if one is computing a 95% confidence interval for each of the samples, the tabled critical two-tailed value $M_{.05} = .563$ for $n_j = n_1 = n_2 = 5$ is employed to represent $M_{\alpha/2}$ in Equation 7.1.

Note the notation $S_j(X)$ is used to represent the points on a cumulative probability distribution for the **Kolmogorov–Smirnov test for two independent samples**, while the notation $S(X_i)$ is used to represent the points on the cumulative probability distribution for the sample evaluated with the **Kolmogorov–Smirnov goodness-of-fit test for a single sample**. In the case of the latter test, there is only one sample for which a confidence interval can be computed, while in the case of the **Kolmogorov–Smirnov test for two independent samples**, a confidence interval can be constructed for each of the independent samples.

3. Large sample chi-square approximation for a one-tailed analysis for the Kolmogorov–Smirnov test for two independent samples Siegel and Castellan (1988) note that Goodman (1954) has shown that Equation 13.1 (which employs the chi-square distribution) can provide a good approximation for large sample sizes when a one-tailed/nondirectional alternative hypothesis is evaluated.³

$$\chi^2 = 4M^2 \left(\frac{n_1 n_2}{n_1 + n_2} \right) \quad (\text{Equation 13.1})$$

The computed value of chi-square is evaluated with [Table A4 \(Table of the Chi-Square Distribution\)](#) in the **Appendix**. The degrees of freedom employed in the analysis will always be $df = 2$. The tabled critical one-tailed .05 and .01 chi-squared values in [Table A4](#) for $df = 2$ are $\chi^2_{.05} = 5.99$ and $\chi^2_{.01} = 9.21$. If the computed value of chi-square is equal to or greater than either of the aforementioned values, the null hypothesis can be rejected at the appropriate level of significance (i.e., the directional alternative hypothesis that is consistent with the data will be supported). Although our sample size is too small for the large sample approximation, for purposes of illustration we will use it. When the appropriate values for Example 13.1 are substituted in Equation 13.1, the value $\chi^2 = 6.4$ is computed. Since $\chi^2 = 6.4$ is larger than $\chi^2_{.05} = 5.99$ but less than $\chi^2_{.01} = 9.21$, the null hypothesis can be rejected, but only at the .05 level. Thus, the directional alternative hypothesis $H_1: F_1(X) > F_2(X)$ is supported at the .05 level. Note that when the tabled critical values in [Table A23](#) are employed, the latter alternative hypothesis is also supported at the .01 level. The latter is consistent with the fact that Siegel and Castellan (1988) note that when Equation 13.1 is employed with small samples sizes, it tends to yield a conservative result (i.e., it is less likely to reject a false null hypothesis).

$$\chi^2 = 4(.80)^2 \left(\frac{(5)(5)}{5 + 5} \right) = 6.4$$

VII. Additional Discussion of the Kolmogorov–Smirnov Test for Two Independent Samples

1. Additional comments on the Kolmogorov–Smirnov test for two independent samples

a) Daniel (1990) states that if for both populations a continuous dependent variable is evaluated, the **Kolmogorov–Smirnov test for two independent samples** yields exact probabilities. He notes, however, that Noether (1963, 1967) has demonstrated that if a discrete dependent variable is evaluated, the test tends to be conservative (i.e., is less likely to reject a false null hypothesis); b) Sprent (1993) notes that the **Kolmogorov–Smirnov test for two independent samples** may not be as powerful as tests that focus on whether or not there is a difference on a specific distributional characteristic such as a measure of central tendency and/or variability. Siegel and Castellan (1988) state that the **Kolmogorov–Smirnov test for two independent samples** is more powerful than the **chi-square test for $r \times c$ tables (Test 16)** and the **median test for independent samples (Test 16e)**. They also note that for small sample sizes, the **Kolmogorov–Smirnov test** has a higher power efficiency than the **Mann–Whitney U test**, but as the sample size increases the opposite becomes true with regard to the power efficiency of the two tests; and c) Conover (1980, 1999) and Hollander and Wolfe (1999) provide a more detailed discussion of the theory underlying the **Kolmogorov–Smirnov test for two independent samples**.

VIII. Additional Examples Illustrating the Kolmogorov–Smirnov Test for Two Independent Samples

Since Examples 11.4 and 11.5 in Section VIII of the **t test for two independent samples** employ the same data as Example 13.1, the **Kolmogorov–Smirnov test for two independent samples** will yield the same result if employed to evaluate the latter two examples. In addition, the **Kolmogorov–Smirnov test** can be employed to evaluate Examples 11.2 and 11.3. Since different data are employed in the latter examples, the result obtained with the **Kolmogorov–Smirnov test** will not be the same as that obtained for Example 13.1. Example 11.2 is evaluated below with the **Kolmogorov–Smirnov test for two independent samples**. Table 13.2 summarizes the analysis.

Table 13.2 Calculation of Test Statistic for Kolmogorov–Smirnov Test for Two Independent Samples for Example 11.2

A (X_1)	B $S_1(X)$	C (X_2)	D $S_2(X)$	E $S_1(X) - S_2(X)$
–	0	7	$1/5 = .20$	$0 - .20 = -.20$
8	$1/5 = .20$	8, 8	$3/5 = .60$	$.20 - .60 = -.40$
9	$2/5 = .40$	9, 9	$5/5 = 1.00$	$.40 - 1.00 = -.60$
10, 10	$4/5 = .80$	–	$5/5 = 1.00$	$.80 - 1.00 = -.20$
11	$5/5 = 1.00$	–	$5/5 = 1.00$	$1.00 - 1.00 = .00$

The obtained value of test statistic is $M = .60$, since .60 is the largest absolute value for a difference score recorded in **Column E** of Table 13.2. Since $n_1 = 5$ and $n_2 = 5$, we employ the same critical values used in evaluating Example 13.1. If the nondirectional alternative hypothesis $H_1: F_1(X) \neq F_2(X)$ is employed, the null hypothesis cannot be rejected at the .05 level, since $M = .60$ is less than the tabled critical two-tailed value $M_{.05} = .800$. The data are consistent with the directional alternative hypothesis $H_1: F_1(X) < F_2(X)$ since in **Row 3** of Table 13.2 [$S_1(X) = .40$] < [$S_2(X) = 1$]. In other words, for the computed value of M , the cumulative proportion for Sample 2 is larger than the cumulative proportion for Sample 1. The directional alternative hypothesis $H_1: F_1(X) < F_2(X)$ is supported at the .05 level, since $M = .60$ is equal to the tabled critical one-tailed value $M_{.05} = .600$. It is not, however, supported at the .01 level, since $M = .60$ is less than the tabled critical one-tailed value $M_{.01} = .800$. The directional alternative hypothesis $H_1: F_1(X) > F_2(X)$ is not supported, since it is not consistent with the data.

When the null hypothesis $H_0: \mu_1 = \mu_2$ is evaluated with the ***t* test for two independent samples**, the only alternative hypothesis which is supported (but only at the .05 level) is the directional alternative hypothesis $H_1: \mu_1 > \mu_2$. The latter result (indicating higher scores in Group 1) is consistent with the result that is obtained when the **Kolmogorov–Smirnov test for two independent samples** is employed to evaluate the same set of data.

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Endnotes

1. Marascuilo and McSweeney (1977) employ a modified protocol that can result in a larger absolute value for *M* in **Column E** than the one obtained in [Table 13.1](#). The latter protocol employs a separate row for the score of each subject when the same score occurs more than once within a group. If the latter protocol is employed in [Table 13.1](#), the first two rows of the table will have the score of 0 in **Column A** for the two subjects in Group 1 who obtain that score. The first 0 will be in the first row, and have a cumulative proportion in **Column B** of

$1/5 = .20$. The second 0 will be in the second row, and have a cumulative proportion in **Column B** of $2/5 = .40$. In the same respect the first of the two scores of 11 (obtained by two subjects in Group 2) will be in a separate row in **Column C**, and have a cumulative proportion in **Column D** of $4/5 = .80$. The second score of 11 will be in the last row of the table, and have a cumulative proportion in **Column D** of $5/5 = 1$. In the case of Example 13.1, the outcome of the analysis will not be affected if the aforementioned protocol is employed. In some instances, however, it can result in a larger M value. The protocol employed by Marascuilo and McSweeney (1977) is used by sources who argue that when there are ties present in the data (i.e., the same score occurs more than once within a group), the protocol described in this chapter (which is used in most sources) results in an overly conservative test (i.e., makes it more difficult to reject a false null hypothesis).

2. When the values of n_1 and n_2 are small, some of the .05 and .01 critical values listed in **Table A23** are identical to one another.
3. The last row in **Table A23** can also be employed to compute a critical M value for large sample sizes.

Test 14

The Siegel–Tukey Test for Equal Variability (Nonparametric Test Employed with Ordinal Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test Do two independent samples represent two populations with different variances?

Relevant background information on test Developed by Siegel and Tukey (1960), the **Siegel–Tukey test for equal variability** is employed with ordinal (rank-order) data in a hypothesis testing situation involving two independent samples. If the result of the **Siegel–Tukey test for equal variability** is significant, it indicates there is a significant difference between the sample variances, and as a result of the latter the researcher can conclude there is a high likelihood that the samples represent populations with different variances.

The **Siegel–Tukey test for equal variability** is one of a number of tests of **dispersion** (also referred to as tests of **scale** or **spread**) that have been developed for contrasting the variances of two independent samples. A discussion of alternative nonparametric tests of dispersion can be found in Section VII. Some sources recommend the use of nonparametric tests of dispersion for evaluating the homogeneity of variance hypothesis when there is reason to believe that the normality assumption of the appropriate parametric test for evaluating the same hypothesis is violated. Sources that are not favorably disposed toward nonparametric tests recommend the use of **Hartley's F_{\max} test for homogeneity of variance/ F test for two population variances (Test 11a)** (or one of the alternative parametric tests that are available for evaluating homogeneity of variance), regardless of whether or not the normality assumption of the parametric test is violated. Such sources do, however, recommend that in employing a parametric test, a researcher employ a lower significance level to compensate for the fact that violation of the normality assumption can inflate the Type I error rate associated with the test. When there is no evidence to indicate that the normality assumption of the parametric test has been violated, sources are in general agreement that such a test is preferable to the **Siegel–Tukey test for equal variability** (or an alternative nonparametric test of dispersion), since a parametric test (which uses more information than a nonparametric test) provides a more powerful test of an alternative hypothesis.

Since nonparametric tests are not assumption free, the choice of which of the available tests of dispersion to employ will primarily depend on what assumptions a researcher is willing to make with regard to the underlying distributions represented by the sample data. The **Siegel–Tukey test for equal variability** is based on the following assumptions: a) Each sample has been randomly selected from the population it represents; b) The two samples are independent of one another; c) The level of measurement the data represent is at least ordinal; and d) The two populations from which the samples are derived have equal medians. If the latter assumption is violated, but the researcher does know the values of the population medians, the scores in the groups can be adjusted so as to allow the use of the **Siegel–Tukey test for equal variability**. When, however, the population medians are unknown, and one is unwilling to assume they are

equal, the **Siegel–Tukey test for equal variability** is not the appropriate nonparametric test of dispersion to employ. The assumption of equality of population medians presents a practical problem, in that when evaluating two independent samples a researcher will often have no prior knowledge regarding the population medians. In point of fact, most hypothesis testing addresses the issue of whether or not the medians (or means) of two or more populations are equal. In view of this, sources such as Siegel and Castellan (1988) note that if the latter values are not known, it is not appropriate to estimate them with the sample medians.

In employing the **Siegel–Tukey test for equal variability**, one of the following is true with regard to the rank-order data that are evaluated: a) The data are in a rank-order format, since it is the only format in which scores are available; or b) The data have been transformed to a rank-order format from an interval/ratio format, since the researcher has reason to believe that the normality assumption of the analogous parametric test is saliently violated.

II. Example

Example 14.1 *In order to assess the effect of two antidepressant drugs, 12 clinically depressed patients are randomly assigned to one of two groups. Six patients are assigned to Group 1, which is administered the antidepressant drug Elatrix for a period of six months. The other six patients are assigned to Group 2, which is administered the antidepressant drug Euphryia during the same six-month period. Assume that prior to introducing the experimental treatments, the experimenter confirmed that the level of depression in the two groups was equal. After six months elapse, all 12 subjects are rated by a psychiatrist (who is blind with respect to a subject's experimental condition) on their level of depression. The psychiatrist's depression ratings for the six subjects in each group follow (the higher the rating, the more depressed a subject):*
Group 1: 10, 10, 9, 1, 0, 0; **Group 2:** 6, 6, 5, 5, 4, 4.

*The fact that the mean and median of each group are equivalent (specifically, both values equal 5) is consistent with prior research which suggests that there is no difference in efficacy for the two drugs (when the latter is based on a comparison of group means and/or medians). Inspection of the data does suggest, however, that there is much greater variability in the depression scores of subjects in Group 1. To be more specific, the data suggest that the drug Elatrix may, in fact, decrease depression in some subjects, yet increase it in others. The researcher decides to contrast the variability within the two groups through use of the **Siegel–Tukey test for equal variability**. The use of the latter nonparametric test is predicated on the fact that there is reason to believe that the distributions of the posttreatment depression scores in the underlying populations are not normal (which is why the researcher is reluctant to evaluate the data with **Hartley's F_{max} test for homogeneity of variance/F test for two population variances**). Do the data indicate there is a significant difference between the variances of the two groups?*

III. Null versus Alternative Hypotheses

Null hypothesis $H_0: \sigma_1^2 = \sigma_2^2$

(The variance of the population Group 1 represents equals the variance of the population Group 2 represents. With respect to the sample data, when both groups have an equal sample size, this translates into the sum of the ranks of Group 1 being equal to the sum of the ranks of Group 2 (i.e., $\sum R_1 = \sum R_2$). A more general way of stating this, which also encompasses designs involving unequal sample sizes, is that the means of the ranks of the two groups are equal (i.e., $R_1 = R_2$)).

Alternative hypothesis

$$H_1: \sigma_1^2 \neq \sigma_2^2$$

(The variance of the population Group 1 represents does not equal the variance of the population Group 2 represents. With respect to the sample data, when both groups have an equal sample size, this translates into the sum of the ranks of Group 1 not being equal to the sum of the ranks of Group 2 (i.e., $\sum R_1 \neq \sum R_2$). A more general way of stating this, which also encompasses designs involving unequal sample sizes, is that the means of the ranks of the two groups are not equal (i.e., $\bar{R}_1 \neq \bar{R}_2$). This is a **nondirectional alternative hypothesis** and it is evaluated with a **two-tailed test**.)

or

$$H_1: \sigma_1^2 > \sigma_2^2$$

(The variance of the population Group 1 represents is greater than the variance of the population Group 2 represents. With respect to the sample data, when both groups have an equal sample size (so long as a rank of 1 is given to the lowest score), this translates into the sum of the ranks of Group 1 being less than the sum of the ranks of Group 2 (i.e., $\sum R_1 < \sum R_2$). A more general way of stating this, which also encompasses designs involving unequal sample sizes, is that the mean of the ranks of Group 1 is less than the mean of the ranks of Group 2 (i.e., $\bar{R}_1 < \bar{R}_2$). This is a **directional alternative hypothesis** and it is evaluated with a **one-tailed test**.)

or

$$H_1: \sigma_1^2 < \sigma_2^2$$

(The variance of the population Group 1 represents is less than the variance of the population Group 2 represents. With respect to the sample data, when both groups have an equal sample size (so long as a rank of 1 is given to the lowest score), this translates into the sum of the ranks of Group 1 being greater than the sum of the ranks of Group 2 (i.e., $\sum R_1 > \sum R_2$). A more general way of stating this, which also encompasses designs involving unequal sample sizes, is that the mean of the ranks of Group 1 is greater than the mean of the ranks of Group 2 (i.e., $\bar{R}_1 > \bar{R}_2$). This is a **directional alternative hypothesis** and it is evaluated with a **one-tailed test**.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis is rejected.

IV. Test Computations

The total number of subjects employed in the experiment is $N = 12$. There are $n_1 = 6$ subjects in Group 1 and $n_2 = 6$ subjects in Group 2. The data for the analysis are summarized in [Table 14.1](#). The original interval/ratio scores of the subjects are recorded in the columns labelled X_1 and X_2 . The adjacent columns R_1 and R_2 contain the rank-order assigned to each of the scores. The rankings for Example 14.1 are summarized in [Table 14.2](#). The ranking protocol for the **Siegel–Tukey test for equal variability** is described in this section. Note that in [Table 14.1](#) and [Table 14.2](#) each subject's identification number indicates the order in [Table 14.1](#) in which a subject's score appears in a given group, followed by his/her group. Thus, Subject i, j is the i^{th} subject in Group j .

The computational procedure for the **Siegel–Tukey test for equal variability** is identical to that employed for the **Mann–Whitney U test (Test 12)**, except for the fact that the two tests employ a different ranking protocol. Recollect that in the description of the alternative hypotheses for the **Siegel–Tukey test for equal variability**, it is noted that when a directional

Table 14.1 Data for Example 14.1

	Group 1			Group 2	
	X_1	R_1		X_2	R_2
Subject 1,1	10	2.5	Subject 1,2	6	8.5
Subject 2,1	10	2.5	Subject 2,2	6	8.5
Subject 3,1	9	6	Subject 3,2	5	11.5
Subject 4,1	1	5	Subject 4,2	5	11.5
Subject 5,1	0	2.5	Subject 5,2	4	8.5
Subject 6,1	0	2.5	Subject 6,2	4	8.5
		$\Sigma R_1 = 21$			$\Sigma R_2 = 57$
		$\bar{R}_1 = \frac{\Sigma R_1}{n_1} = \frac{21}{6} = 3.5$			$\bar{R}_2 = \frac{\Sigma R_2}{n_2} = \frac{57}{6} = 9.5$

Table 14.2 Rankings for the Siegel–Tukey Test for Equal Variability for Example 14.1

Subject identification number	5,1	6,1	4,1	5,2	6,2	3,2	4,2	1,2	2,2	3,1	1,1	2,1
Depression score	0	0	1	4	4	5	5	6	6	9	10	10
Rank prior to tie adjustment	1	4	5	8	9	12	11	10	7	6	3	2
Tie-adjusted rank	2.5	2.5	5	8.5	8.5	11.5	11.5	8.5	8.5	6	2.5	2.5

alternative hypothesis is supported, the average of the ranks of the group with the larger variance will be **less** than the average of the ranks of the group with the smaller variance. On the other hand, when a directional hypothesis for the **Mann–Whitney U test** is supported, the average of the ranks of the group with the larger median will be greater than the average of the ranks of the group with the smaller median. The difference between the two tests with respect to the ordinal position of the average ranks reflects the fact that the tests employ different ranking protocols. Whereas the ranking protocol for the **Mann–Whitney U test** is designed to identify differences with respect to central tendency (specifically, the median values), the ranking protocol for the **Siegel–Tukey test for equal variability** is designed to identify differences with respect to variability. The ranking protocol for the **Siegel–Tukey test for equal variability** is based on the premise that within the overall distribution of N scores, the distribution of scores in the group with the higher variance will contain more extreme values (i.e., scores that are very high and scores that are very low) than the distribution of scores in the group with the lower variance.

The following protocol, which is summarized in [Table 14.2](#), is used in assigning ranks.

a) All $N = 12$ scores are arranged in order of magnitude (irrespective of group membership), beginning on the left with the lowest score and moving to the right as scores increase. This is done in the second row of [Table 14.2](#).

b) Ranks are now assigned in the following manner: A rank of 1 is assigned to the lowest score (0). A rank of 2 is assigned to the highest score (10), and a rank of 3 is assigned to the second highest score (10). A rank of 4 is assigned to the second lowest score (0), and a rank of 5 is assigned to the third lowest score (1). A rank of 6 is assigned to the third highest score (9), and a rank of 7 is assigned to the fourth highest score (6). A rank of 8 is assigned to the fourth lowest score (4), and a rank of 9 is assigned to the fifth lowest score (4). A rank of 10 is assigned to the fifth highest score (6), and a rank of 11 is assigned to the sixth highest score (5). A rank of 12 is assigned to the sixth lowest score (5). Note that the ranking protocol assigns ranks to the distribution of $N = 12$ scores by alternating from one extreme of the distribution to the other. The ranks assigned employing this protocol are listed in the third row of [Table 14.2](#)

c) The ranks in the third row of [Table 14.2](#) must be adjusted when there are tied scores present in the data. The same procedure for handling ties that is described for the **Mann–Whitney U test** is also employed with for **Siegel–Tukey test for equal variability**. Specifically, in instances where two or more subjects have the same score, the average of the ranks involved is assigned to all scores tied for a given rank. This adjustment is made in the fourth row of [Table 14.2](#). To illustrate: Both Subjects 5,1 and 6,1 have a score of 0. Since the ranks assigned to the scores of these two subjects are, respectively, 1 and 4, the average of the two ranks $(1 + 4)/2 = 2.5$ is assigned to the score of both subjects. Both Subjects 1,1 and 2,1 have a score of 10. Since the ranks assigned to the score of these two subjects are, respectively, 2 and 3, the average of the two ranks $(2 + 3)/2 = 2.5$ is assigned to the score of both subjects. For the remaining three sets of ties (which all happen to fall in Group 2) the same averaging procedure is employed.

It should be noted that in Example 14.1 each set of tied scores involves subjects who are in the same group. Any time each set of ties involves subjects in the same group, the tie adjustment will result in the identical sum and average for the ranks of the two groups that will be obtained if the tie adjustment is not employed. Because of this, under these conditions the computed test statistic will be identical regardless of whether or not one uses the tie adjustment. On the other hand, when one or more sets of ties involve subjects from both groups, the tie-adjusted ranks will yield a value for the test statistic that is different from that which will be obtained if the tie adjustment is not employed.

It should be noted that it is permissible to reverse the ranking protocol described in this section. Specifically, one can assign a rank of 1 to the highest score, a rank of 2 to the lowest score, a rank of 3 to the second lowest score, a rank of 4 to the second highest score, a rank of 5 to the third highest score, and so on. This reverse-ranking protocol will result in the same test statistic and, consequently, the same conclusion with respect to the null hypothesis as the ranking protocol described in this section.¹

Once all of the subjects have been assigned a rank, the sum of the ranks for each of the groups is computed. These values, $\sum R_1 = 21$ and $\sum R_2 = 57$, are computed in [Table 14.1](#). Upon determining the sum of the ranks for both groups, the values U_1 and U_2 are computed using Equations 12.1 and 12.2, which are employed for the **Mann–Whitney U test**. The basis for employing the same equations and the identical distribution as that used for the **Mann–Whitney U test** is predicated on the fact that both tests employ the same sampling distribution.

$$U_1 = n_1 n_2 + \frac{n_1(n_1 + 1)}{2} - \sum R_1 = (6)(6) + \frac{6(6 + 1)}{2} - 21 = 36$$

$$U_2 = n_1 n_2 + \frac{n_2(n_2 + 1)}{2} - \sum R_2 = (6)(6) + \frac{6(6 + 1)}{2} - 57 = 0$$

Note that U_1 and U_2 can never be negative values. If a negative value is obtained for either, it indicates an error has been made in the rankings and/or calculations.

As is the case for the **Mann–Whitney U test**, Equation 12.3 can be employed to verify the calculations. If the relationship in Equation 12.3 is not confirmed, it indicates that an error has been made in ranking the scores or in the computation of the U values. The relationship described by Equation 12.3 is confirmed below for Example 14.1.

$$n_1 n_2 = U_1 + U_2$$

$$(6)(6) = 36 + 0 = 36$$

V. Interpretation of the Test Results

The smaller of the two values U_1 versus U_2 is designated as the obtained U statistic. Since $U_2 = 0$ is smaller than $U_1 = 36$, the value of $U = 0$. The value of U is evaluated with [Table A11 \(Table of Critical Values for the Mann–Whitney \$U\$ Statistic\)](#) in the [Appendix](#). In order to be significant, the obtained value of U must be **equal to or less than** the tabled critical value at the prespecified level of significance. For $n_1 = 6$ and $n_2 = 6$, the tabled critical two-tailed values are $U_{.05} = 5$ and $U_{.01} = 2$, and the tabled critical one-tailed values are $U_{.05} = 7$ and $U_{.01} = 3$.²

Since the obtained value $U = 0$ is less than the tabled critical two-tailed values $U_{.05} = 5$ and $U_{.01} = 2$, the nondirectional alternative hypothesis $H_1: \sigma_1^2 \neq \sigma_2^2$ is supported at both the .05 and .01 levels. Since the obtained value of U is less than the tabled critical one-tailed values $U_{.05} = 7$ and $U_{.01} = 3$, the directional alternative hypothesis $H_1: \sigma_1^2 > \sigma_2^2$ is also supported at both the .05 and .01 levels. The latter directional alternative hypothesis is supported since $R_1 < R_2$, which indicates that the variability of scores in Group 1 is greater than the variability of scores in Group 2. The directional alternative hypothesis $H_1: \sigma_1^2 < \sigma_2^2$ is not supported, since in order for the latter alternative hypothesis to be supported, R_1 must be greater than R_2 (which indicates that the variability of scores in Group 2 is greater than the variability of scores in Group 1).

Based on the results of the **Siegel–Tukey test for equal variability**, the researcher can conclude that there is greater variability in the depression scores of the group that receives the drug Elatrix (Group 1) than the group that receives the drug Euphyria (Group 2).

VI. Additional Analytical Procedures for the Siegel–Tukey Test for Equal Variability and/or Related Tests

1. The normal approximation of the Siegel–Tukey test statistic for large sample sizes As is the case with the **Mann–Whitney U test**, the normal distribution can be employed with large sample sizes to approximate the **Siegel–Tukey test** statistic. Equation 12.4, which is employed for the large sample approximation of the **Mann–Whitney distribution**, can also be employed for the large sample approximation of **Siegel–Tukey test** statistic. As is noted in Section VI of the **Mann–Whitney U test**, the large sample approximation is generally used for sample sizes larger than those documented in the exact table contained within the source one is employing.

In the discussion of the **Mann–Whitney U test**, it is noted that the term $(n_1 n_2)/2$ in the numerator of Equation 12.4 represents the expected (mean) value of U if the null hypothesis is true. This is also the case when the normal distribution is employed to approximate the **Siegel–Tukey test statistic**. Thus, if the two population variances are in fact equal, it is expected that $R_1 = R_2$ and, consequently, $U_1 = U_2 = (n_1 n_2)/2$.

Although Example 14.1 involves only $N = 12$ scores (a value most sources would view as too small to use with the normal approximation), it will be employed to illustrate Equation 12.4. The reader will see that in spite of employing Equation 12.4 with a small sample size, it yields a result that is consistent with the result obtained when the exact table for the **Mann–Whitney U distribution** is employed. As is noted in Section VI of the **Mann–Whitney U test**, since the smaller of the two values U_1 versus U_2 is selected to represent U , the value of z will always be negative (unless $U_1 = U_2$, in which case $z = 0$).

Employing Equation 12.4, the value $z = -2.88$ is computed.

$$z = \frac{U - \frac{n_1 n_2}{2}}{\sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12}}} = \frac{0 - \frac{(6)(6)}{2}}{\sqrt{\frac{(6)(6)(6 + 6 + 1)}{12}}} = -2.88$$

The obtained value $z = -2.88$ is evaluated with **Table A1 (Table of the Normal Distribution)** in the **Appendix**. To be significant, the obtained absolute value of z must be equal to or greater than the tabled critical value at the prespecified level of significance. The tabled critical two-tailed .05 and .01 values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed .05 and .01 values are $z_{.05} = 1.65$ and $z_{.01} = 2.33$. The following guidelines are employed in evaluating the null hypothesis.

a) If the nondirectional alternative hypothesis $H_1: \sigma_1^2 \neq \sigma_2^2$ is employed, the null hypothesis can be rejected if the obtained absolute value of z is equal to or greater than the tabled critical two-tailed value at the prespecified level of significance.

b) If a directional alternative hypothesis is employed, one of the two possible directional alternative hypotheses is supported if the obtained absolute value of z is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance. The directional alternative hypothesis that is supported is the one that is consistent with the data.

Employing the above guidelines with Example 14.1, the following conclusions are reached.

Since the obtained absolute value $z = 2.88$ is greater than the tabled critical two-tailed values $z_{.05} = 1.96$ and $z_{.01} = 2.58$, the nondirectional alternative hypothesis $H_1: \sigma_1^2 \neq \sigma_2^2$ is supported at the both the .05 and .01 levels. Since the obtained absolute value $z = 2.88$ is greater than the tabled critical one-tailed values $z_{.05} = 1.65$ and $z_{.01} = 2.33$, the directional alternative hypothesis $H_1: \sigma_1^2 > \sigma_2^2$ is supported at both the .05 and .01 levels. The latter directional alternative hypothesis is supported since it is consistent with the data. The directional alternative hypothesis $H_1: \sigma_1^2 < \sigma_2^2$ is not supported, since it is not consistent with the data. Note that the conclusions reached with reference to each of the possible alternative hypotheses are consistent with those reached when the exact table of the U distribution is employed.

As is the case when normal approximation is used with the **Mann–Whitney U test**, either U_1 or U_2 can be employed in Equation 12.4 to represent the value of U , since both values will yield the same absolute value for z .

2. The correction for continuity for the normal approximation of the Siegel–Tukey test for equal variability Although not described in most sources, the correction for continuity employed for the normal approximation of the **Mann–Whitney U test** can also be applied to the **Siegel–Tukey test for equal variability**. Employing Equation 12.5 (the **Mann–Whitney continuity-corrected equation**) with the data for Example 14.1, the value $z = -2.80$ is computed.

$$z = \frac{\left| U - \frac{n_1 n_2}{2} \right| - .5}{\sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12}}} = \frac{\left| 0 - \frac{(6)(6)}{2} \right| - .5}{\sqrt{\frac{(6)(6)(6 + 6 + 1)}{12}}} = -2.80$$

The obtained absolute value $z = 2.80$ is greater than the tabled critical two-tailed .05 and .01 values $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed .05 and .01 values

$z_{.05} = 1.65$ and $z_{.01} = 2.33$. Thus, as is the case when the correction for continuity is not employed, both the nondirectional alternative hypothesis $H_1: \sigma_1^2 \neq \sigma_2^2$ and the directional alternative hypothesis $H_1: \sigma_1^2 > \sigma_2^2$ are supported at both the .05 and .01 levels. Note that the absolute value of the continuity-corrected z value will always be less than the absolute value computed when the correction for continuity is not used.

3. Tie correction for the normal approximation of the Siegel–Tukey test statistic It is noted in the discussion of the normal approximation of the **Mann–Whitney U test** that some sources recommend that Equation 12.4 be modified when an excessive number of ties are present in the data. Since the identical sampling distribution is involved, the same tie correction (which results in a slight increase in the absolute value of z) can be employed for the normal approximation of the **Siegel–Tukey test for equal variability**. Employing Equation 12.6 (the **Mann–Whitney tie correction equation**), the tie-corrected value $z = -2.91$ is computed for Example 14.1. Note that in Example 14.1 there are $s = 5$ sets of ties, each set involving two ties. Thus, in Equation 12.6 the term $\sum_{i=1}^s (t_i^3 - t_i) = 5[(2)^3 - 2] = 30$.

$$\begin{aligned}
 z &= \frac{U - \frac{n_1 n_2}{2}}{\sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12} - \frac{n_1 n_2 \left[\sum_{i=1}^s (t_i^3 - t_i) \right]}{12(n_1 + n_2)(n_1 + n_2 - 1)}}} \\
 &= \frac{0 - \frac{(6)(6)}{2}}{\sqrt{\frac{(6)(6)(6 + 6 + 1)}{12} - \frac{(6)(6)(30)}{12(6 + 6)(6 + 6 - 1)}}} = -2.91
 \end{aligned}$$

The difference between $z = -2.91$ and the uncorrected value $z = -2.88$ is trivial, and consequently the decision the researcher makes with respect to the null hypothesis is not affected, regardless of which alternative hypothesis is employed.

4. Adjustment of scores for the Siegel–Tukey test for equal variability when $\theta_1 \neq \theta_2$ It is noted in Section I that if the values of the population medians are known but are not equal, in order to employ the **Siegel–Tukey test for equal variability** it is necessary to adjust the scores. In such a case, prior to ranking the scores the difference between the two population medians is subtracted from each of the scores in the group that represents the population with the higher median (or added to each of the scores in the group that represents the population with the lower median). This adjustment procedure will be demonstrated with Example 14.2.

Example 14.2 *In order to evaluate whether or not two teaching methods result in different degrees of variability with respect to performance, a mathematics instructor employs two methods of instruction with different groups of students. Prior to initiating the study it is determined that the two groups are comprised of students of equal math ability. Group 1, which is comprised of five subjects, is taught through the use of lectures and a conventional textbook (Method A). Group 2, which is comprised of six subjects, is taught through the use of a computer software package (Method B). At the conclusion of the course the final exam scores of the two groups are compared. The final exam scores follow (the maximum possible score on the final*

exam is 10 points and the minimum 0): **Group 1:** 7, 5, 4, 4, 3; **Group 2:** 13, 12, 7, 7, 4, 3. The researcher elects to rank-order the scores of the subjects, since she does not believe the data are normally distributed in the underlying populations. If the **Siegel–Tukey test for equal variability** is employed to analyze the data, is there a significant difference in within-groups variability?

From the sample data we can determine that the median score of Group 1 is 4, and the median score of Group 2 is 7. Although the computations will not be shown here, in spite of the three-point difference between the medians of the groups, if the **Mann–Whitney *U* test** is employed to evaluate the data, the null hypothesis $H_0: \theta_1 = \theta_2$ (i.e., that the medians of the underlying populations are equal) cannot be rejected at the .05 level, regardless of whether a nondirectional or directional alternative hypothesis is employed. The fact that the null hypothesis cannot be rejected is largely the result of the small sample size, which limits the power of the **Mann–Whitney *U* test** to detect a difference between underlying populations, if, in fact, one exists.

Let us assume, however, that based on prior research there is reason to believe that the median of the population represented by Group 2 is, in fact, three points higher than the median of the population represented by Group 1. In order to employ the **Siegel–Tukey test for equal variability** to evaluate the null hypothesis $H_0: \sigma_1^2 = \sigma_2^2$, the groups must be equated with respect to their median values. This can be accomplished by subtracting the difference between the population medians from each score in the group with the higher median. Thus, in [Table 14.3](#) three points have been subtracted from the score of each of the subjects in Group 2.³ The scores in [Table 14.3](#) are ranked in accordance with the **Siegel–Tukey test** protocol. The ranks are summarized in [Table 14.4](#).

Table 14.3 Data for Example 14.2 Employing Adjusted *X*₂ Scores

	Group 1			Group 2	
	<i>X</i> ₁	<i>R</i> ₁		<i>X</i> ₂	<i>R</i> ₂
Subject 1,1	7	6	Subject 1,2	10	2
Subject 2,1	5	7	Subject 2,2	9	3
Subject 3,1	4	9.5	Subject 3,2	4	9.5
Subject 4,1	4	9.5	Subject 4,2	4	9.5
Subject 5,1	3	5	Subject 5,2	1	4
			Subject 6,2	0	1
	$\Sigma R_1 = 37$			$\Sigma R_2 = 29$	
	$\bar{R}_1 = \frac{\Sigma R_1}{n_1} = \frac{37}{5} = 7.4$			$\bar{R}_2 = \frac{\Sigma R_2}{n_2} = \frac{29}{6} = 4.83$	

Table 14.4 Rankings for the Siegel–Tukey Test for Equal Variability for Example 14.2

Subject identification number	6,2	5,2	5,1	3,1	4,1	3,2	4,2	2,1	1,1	2,2	1,2
Exam score	0	1	3	4	4	4	4	5	7	9	10
Rank prior to tie adjustment	1	4	5	8	9	11	10	7	6	3	2
Tie-adjusted rank	1	4	5	9.5	9.5	9.5	9.5	7	6	3	2

Equations 12.1 and 12.2 are employed to compute the values $U_1 = 8$ and $U_2 = 22$.

$$U_1 = n_1 n_2 + \frac{n_1(n_1 + 1)}{2} - \Sigma R_1 = (5)(6) + \frac{5(5 + 1)}{2} - 37 = 8$$

$$U_2 = n_1 n_2 + \frac{n_2(n_2 + 1)}{2} - \Sigma R_2 = (5)(6) + \frac{6(6 + 1)}{2} - 29 = 22$$

Employing Equation 12.3, we confirm the relationship between the sample sizes and the computed values of U_1 and U_2 .

$$\begin{aligned} n_1 n_2 &= U_1 + U_2 \\ (5)(6) &= 8 + 22 = 30 \end{aligned}$$

Since $U_1 = 8$ is smaller than $U_2 = 22$, the value of $U = 8$. Employing [Table A11](#) for $n_1 = 5$ and $n_2 = 6$, we determine that the tabled critical two-tailed .05 and .01 values are $U_{.05} = 3$ and $U_{.01} = 1$, and the tabled critical one-tailed .05 and .01 values are $U_{.05} = 5$ and $U_{.01} = 2$. Since the obtained value $U = 8$ is greater than all of the aforementioned tabled critical values, the null hypothesis cannot be rejected at either .05 or .01 level, regardless of whether a nondirectional or directional alternative hypothesis is employed.

If the normal approximation for the **Siegel–Tukey test for equal variability** is employed with Example 14.2, it is also the case that the null hypothesis cannot be rejected, regardless of which alternative hypothesis is employed. The latter is the case, since the computed absolute value $z = 1.28$ is less than the tabled critical .05 and .01 two-tailed values $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical .05 and .01 one-tailed values $z_{.05} = 1.65$ and $z_{.01} = 2.33$.

$$z = \frac{8 - \frac{(5)(6)}{2}}{\sqrt{\frac{(5)(6)(5 + 6 + 1)}{12}}} = -1.28$$

Thus, the data do not indicate that the two teaching methods represent populations with different variances. Of course, as is the case when the **Mann–Whitney U test** is employed with the same set of data, it is entirely possible that a difference does exist in the underlying populations but is not detected because of the small sample size employed in the study.

VII. Additional Discussion of the Siegel–Tukey Test for Equal Variability

1. Analysis of the homogeneity of variance hypothesis for the same set of data with both a parametric and nonparametric test, and the power-efficiency of the Siegel–Tukey test for equal variability As noted in Section I, the use of the **Siegel–Tukey test for equal variability** would most likely be based on the fact that a researcher has reason to believe that the data in the underlying populations are not normally distributed. If, however, in the case of Example 14.1 the normality assumption is not an issue, or if it is but in spite of it a researcher prefers to use a parametric procedure such as **Hartley's F_{\max} test for homogeneity of variance/ F test for two population variances**, she can still reject the null hypothesis $H_0: \sigma_1^2 = \sigma_2^2$ at both the .05 or .01 levels, regardless of whether a nondirectional or directional alternative hypothesis is employed.

This is demonstrated by employing Equation 11.6 (the equation for **Hartley's F_{\max} test for homogeneity of variance**) with the data for Example 14.1.

$$\begin{aligned}\Sigma X_1 &= 30 & \Sigma X_1^2 &= 282 & \Sigma X_2 &= 30 & \Sigma X_2^2 &= 154 \\ \hat{s}_1^2 &= \frac{282 - \frac{(30)^2}{6}}{6 - 1} = 26.4 & \hat{s}_2^2 &= \frac{154 - \frac{(30)^2}{6}}{6 - 1} = .8 \\ F_{\max} &= \frac{\hat{s}_L^2}{\hat{s}_S^2} = \frac{26.4}{.8} = 33\end{aligned}$$

Table A9 (Table of the F_{\max} Distribution) in the **Appendix** is employed to evaluate the computed value $F_{\max} = 33$. For $k = 2$ groups and $(n - 1) = (6 - 1) = 5$ (since $n_1 = n_2 = n = 6$), the appropriate tabled critical values for a nondirectional analysis are $F_{\max_{.05}} = 7.15$ and $F_{\max_{.01}} = 14.9$. Since the obtained value $F_{\max} = 33$ is greater than both of the aforementioned tabled critical values, the nondirectional alternative hypothesis $H_1: \sigma_1^2 \neq \sigma_2^2$ is supported at both the .05 and .01 levels.⁴

In the case of a directional analysis, the appropriate tabled critical one-tailed .05 and .01 values must be obtained from **Table A10 (Table of the F Distribution)** in the **Appendix**. In **Table A10**, the values for $F_{.95}$ and $F_{.99}$ for $df_{\text{num}} = n_1 - 1 = 6 - 1 = 5$ and $df_{\text{den}} = n_2 - 1 = 6 - 1 = 5$ are employed. The appropriate values derived from **Table A10** are $F_{.95} = 5.05$ and $F_{.99} = 10.97$. Since the obtained value $F_{\max} = 33$ is greater than both of the aforementioned tabled critical values, the directional alternative hypothesis $H_1: \sigma_1^2 > \sigma_2^2$ is supported at both the .05 and .01 levels.

Note that the difference between the computed F_{\max} (or F) value and the appropriate tabled critical value is more pronounced in the case of **Hartley's F_{\max} test for homogeneity of variance/ F test for two population variances** than the difference between the computed test statistic and the appropriate tabled critical value for the **Siegel–Tukey test for equal variability** (when either the exact U distribution or the normal approximation is employed). The actual probability associated with the outcome of the analysis is, in fact, less than .01 for both the F_{\max} and **Siegel–Tukey tests**, but is even further removed from .01 in the case of the F_{\max} test. This latter observation is consistent with the fact that when both a parametric and nonparametric test are applied to the same set of data, the former test will generally provide a more powerful test of an alternative hypothesis.

The above outcome is consistent with the fact that various sources (e.g., Marascuilo and McSweeney (1977) and Siegel and Castellan (1988)) note that the **asymptotic relative efficiency** (discussed in Section VII of the **Wilcoxon signed-ranks test (Test 6)**) of the **Siegel–Tukey test** relative to the F_{\max} test is only .61. However, the asymptotic relative efficiency of the **Siegel–Tukey test** may be considerably higher when the underlying population distributions are not normal.

2. Alternative nonparametric tests of dispersion In Section I it is noted that the **Siegel–Tukey test for equal variability** is one of a number of nonparametric tests for ordinal data that have been developed for evaluating the hypothesis that two populations have equal variances. The determination with respect to which of these tests to employ is generally based on the specific assumptions a researcher is willing to make about the underlying population distributions. Other factors that can determine which test a researcher elects to employ are the relative power

efficiencies of the tests under consideration, and the complexity of the computations required for a specific test. This section will briefly summarize a few of the alternative procedures that evaluate the same hypothesis as the **Siegel–Tukey test for equal variability**. One or more of these procedures are described in detail in various books which specialize in nonparametric statistics (e.g., Conover (1980, 1999), Daniel (1990), Hollander and Wolfe (1999), Marascuilo and McSweeney (1977), Siegel and Castellan (1988), and Sprent (1993)). In addition, Sheskin (1984) provides a general overview and bibliography of nonparametric tests of dispersion.

The **Ansari–Bradley test** (Ansari and Bradley (1960) and Freund and Ansari (1957)) evaluates the same hypothesis as the **Siegel–Tukey test for equal variability**, as well as sharing its assumptions. The **Moses test for equal variability (Test 15)** (Moses, 1963), which is described in the next chapter, can also be employed to evaluate the same hypothesis. However, the **Moses test** is more computationally involved than the two aforementioned tests. Unlike the **Siegel–Tukey test** and **Ansari–Bradley test**, the **Moses test** assumes that the data evaluated represent at least interval level measurement. In addition, the **Moses test** does not assume that the two populations have equal medians. Among other nonparametric tests of dispersion are procedures developed by Conover (Conover and Iman (1978), Conover (1980, 1999)), Klotz (1962), and Mood (1954). Of the tests just noted, the **Siegel–Tukey test for equal variability**, the **Klotz test**, and the **Mood test** can be extended to designs involving more than two independent samples. In addition to all of the aforementioned procedures, **tests of extreme reactions** developed by Moses (1952) (the **Moses test of extreme reactions** is described in Siegel (1956)) and Hollander (1963) can be employed to contrast the variability of two independent groups. Since there is extensive literature on nonparametric tests of dispersion, the interested reader should consult sources that specialize in nonparametric statistics for a more comprehensive discussion of the subject.

VIII. Additional Examples Illustrating the Siegel–Tukey Test for Equal Variability

The **Siegel–Tukey test for equal variability** can be employed to evaluate the null hypothesis $H_0: \sigma_1^2 = \sigma_2^2$ with any of the examples noted for the ***t* test for two independent samples (Test 11)** and the **Mann–Whitney *U* test**. In order to employ the **Siegel–Tukey test for equal variability** with any of the aforementioned examples, the data must be rank-ordered employing the protocol described in Section IV. Example 14.3 is an additional example that can be evaluated with the **Siegel–Tukey test for equal variability**. It is characterized by the fact that unlike Examples 14.1 and 14.2, in Example 14.3 subjects are rank-ordered without initially obtaining scores that represent interval/ratio level measurement. Although it is implied that the ranks in Example 14.3 are based on an underlying interval/ratio scale, the data are never expressed in such a format.

Example 14.3 *A company determines that there is no difference with respect to enthusiasm for a specific product after people are exposed to a monochromatic versus a polychromatic advertisement for the product. The company, however, wants to determine whether different degrees of variability are associated with the two types of advertisement. To answer the question, a study is conducted employing twelve subjects who as a result of having no knowledge of the product are neutral towards it. Six of the subjects are exposed to a monochromatic advertisement for the product (Group 1), and the other six are exposed to a polychromatic version of the same advertisement (Group 2). One week later each subject is interviewed by a market researcher who is blind with respect to which advertisement a subject was exposed. Upon*

interviewing all 12 subjects, the market researcher rank-orders them with respect to their level of enthusiasm for the product. The rank-orders of the subjects in the two groups follow (assume that the lower the rank-order, the lower the level of enthusiasm for the product):

Group 1: Subject 1,1: 12; Subject 2,1: 2; Subject 3,1: 4; Subject 4,1: 6;
 Subject 5,1: 3; Subject 6,1: 10
Group 2: Subject 1,2: 7; Subject 2,2: 5; Subject 3,2: 9; Subject 4,2: 8;
 Subject 5,2: 11; Subject 6,2: 1

Is there a significant difference in the degree of variability within each of the groups?

Employing the ranking protocol for the **Siegel–Tukey test for equal variability** with the above data, the ranks of the two groups are converted into the following new set of ranks (i.e., assigning a rank of 1 to the lowest rank, a rank of 2 to the highest rank, a rank of 3 to the second highest rank, etc.).

Group 1: Subject 1,1: 2; Subject 2,1: 4; Subject 3,1: 8; Subject 4,1: 12;
 Subject 5,1: 5; Subject 6,1: 6
Group 2: Subject 1,2: 11; Subject 2,2: 9; Subject 3,2: 7; Subject 4,2: 10;
 Subject 5,2: 3; Subject 6,2: 1

Employing the above set of ranks, $\Sigma R_1 = 37$ and $\Sigma R_2 = 41$. Through use of Equations 12.1 and 12.2, the values of U_1 and U_2 are computed to be $U_1 = (6)(6) + [(6(6 + 1))/2] - 37 = 20$ and $U_2 = (6)(6) + [(6(6 + 1))/2 - 41] = 16$. Since $U_2 = 16$ is less than $U_1 = 20$, $U = 16$. In **Table A11**, for $n_1 = 6$ and $n_2 = 6$, the tabled critical two-tailed .05 and .01 values are $U_{.05} = 5$ and $U_{.01} = 2$, and the tabled critical one-tailed .05 and .01 values are $U_{.05} = 7$ and $U_{.01} = 3$. Since $U = 16$ is greater than all of the aforementioned critical values, the null hypothesis $H_0: \sigma_1^2 = \sigma_2^2$ cannot be rejected, regardless of whether a nondirectional or directional alternative hypothesis is employed. Thus, there is no evidence to indicate that the two types of advertisements result in different degrees of variability.

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Endnotes

1. As is the case with the **Mann–Whitney U test**, if the reverse ranking protocol is employed, the values of U_1 and U_2 are reversed. Since the value of U , which represents the test statistic, is the lower of the two values U_1 versus U_2 , the value designated U with the reverse ranking protocol will be the same U value obtained with the original ranking protocol.
2. As is the case with the **Mann–Whitney U test**, in describing the **Siegel–Tukey test for equal variability** some sources do not compute a U value, but rather provide tables which are based on the smaller and/or larger of the two sums of ranks. The equation for the normal approximation (to be discussed in Section VI) in these sources is also based on the sums of the ranks.
3. As previously noted, we can instead add three points to each score in Group 1.
4. If one employs Equation 11.7, and thus uses **Table A10**, the same tabled critical values are listed for $F_{.975}$ and $F_{.995}$ for $df_{\text{num}} = 6 - 1 = 5$ and $df_{\text{den}} = 6 - 1 = 5$. Thus, $F_{.975} = 7.15$ and $F_{.995} = 14.94$. (The latter value is only listed to one decimal place in **Table A9**.) The use of **Table A10** in evaluating homogeneity of variance is discussed in Section VI of the **t test for two independent samples**.

Test 15

The Moses Test for Equal Variability (Nonparametric Test Employed with Ordinal Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test Do two independent samples represent two populations with different variances?

Relevant background information on test Developed by Moses (1963), the **Moses test for equal variability** is a nonparametric procedure that can be employed in a hypothesis testing situation involving two independent samples. If the result of the **Moses test for equal variability** is significant, it indicates there is a significant difference between the sample variances, and as a result of the latter the researcher can conclude there is a high likelihood that the samples represent populations with different variances.

The **Moses test for equal variability** is one of a number of tests of **dispersion** (also referred to as tests of **scale** or **spread**) that have been developed for contrasting the variances of two independent samples. A discussion of alternative nonparametric tests of dispersion can be found in Section VII. Some sources recommend the use of nonparametric tests of dispersion for evaluating the homogeneity of variance hypothesis when there is reason to believe that the normality assumption of the appropriate parametric test for evaluating the same hypothesis is violated. Sources that are not favorably disposed toward nonparametric tests recommend the use of **Hartley's F_{\max} test for homogeneity of variance/ F test for two population variances (Test 11a)** (or one of the alternative parametric tests that are available for evaluating homogeneity of variance), regardless of whether or not the normality assumption of the parametric test is violated. Such sources do, however, recommend that in employing a parametric test, a researcher employ a lower significance level to compensate for the fact that violation of the normality assumption can inflate the Type I error rate associated with the test. When there is no evidence to indicate that the normality assumption of the parametric test has been violated, sources are in general agreement that such a test is preferable to the **Moses test for equal variability** (or an alternative nonparametric test of dispersion), since a parametric test (which uses more information than a nonparametric test) provides a more powerful test of an alternative hypothesis.

Since nonparametric tests are not assumption free, the choice of which of the available tests of dispersion to employ will primarily depend on what assumptions a researcher is willing to make with regard to the underlying distributions represented by the sample data. The **Moses test for equal variability** is based on the following assumptions: a) Each sample has been randomly selected from the population it represents; b) The two samples are independent of one another; c) The original scores obtained for each of the subjects are in the format of interval/ratio data, and the dependent variable is a **continuous** variable. (A **continuous variable** is characterized by the fact that a given score can assume any value within the range of values that define the limits of that variable.); and d) The underlying populations from which the samples are derived are similar in shape.

It is important to note that a major difference between the **Moses test for equal variability** and the previously discussed **Siegel–Tukey test for equal variability (Test 14)** is that the **Moses test** does not assume that the two populations from which the samples are derived have equal medians (which is an assumption underlying the **Siegel–Tukey test**).

It should be noted that all of the other tests in this text that rank data (with the exception of the **Wilcoxon signed-ranks test (Test 6)** and the **Wilcoxon matched-pairs signed-ranks test (Test 18)**) rank the original interval/ratio scores of subjects. The **Moses test for equal variability**, however, does not rank the original interval/ratio scores, but instead ranks the sums of squared difference/deviation scores. For this reason, some sources (e.g., Siegel and Castellan (1988)) categorize the **Moses test for equal variability** as a test of interval/ratio data. In this book, however, the **Moses test for equal variability** is categorized as a test of ordinal data, by virtue of the fact that a ranking procedure constitutes a critical part of the test protocol.

II. Example

Example 15.1 is identical to Example 14.1 (which is evaluated with the **Siegel–Tukey test for equal variability**). Although Example 15.1 suggests that the underlying population medians are equal, as noted above, the latter is not an assumption of the **Moses test for equal variability**.

Example 15.1 *In order to assess the effect of two antidepressant drugs, 12 clinically depressed patients are randomly assigned to one of two groups. Six patients are assigned to Group 1, which is administered the antidepressant drug Elatrix for a period of six months. The other six patients are assigned to Group 2, which is administered the antidepressant drug Euphryia during the same six-month period. Assume that prior to introducing the experimental treatments, the experimenter confirmed that the level of depression in the two groups was equal. After six months elapse, all 12 subjects are rated by a psychiatrist (who is blind with respect to a subject's experimental condition) on their level of depression. The psychiatrist's depression ratings for the six subjects in each group follow (the higher the rating, the more depressed a subject):*
Group 1: 10, 10, 9, 1, 0, 0; **Group 2:** 6, 6, 5, 5, 4, 4.

*The fact that the mean and median of each group are equivalent (specifically, both values equal 5) is consistent with prior research which suggests that there is no difference in efficacy for the two drugs (when the latter is based on a comparison of group means and/or medians). Inspection of the data does suggest, however, that there is much greater variability in the depression scores of subjects in Group 1. To be more specific, the data suggest that the drug Elatrix may, in fact, decrease depression in some subjects, yet increase it in others. The researcher decides to contrast the variability within the two groups through use of the **Moses test for equal variability**. The use of the latter nonparametric test is predicated on the fact that there is reason to believe that the distributions of the posttreatment depression scores in the underlying populations are not normal (which is why the researcher is reluctant to evaluate the data with **Hartley's F_{max} test for homogeneity of variance/F test for two population variances**). Do the data indicate there is a significant difference between the variances of the two groups?*

III. Null versus Alternative Hypotheses

The test statistic for the **Moses test for equal variability** is computed with the **Mann–Whitney U test (Test 12)**. In order to understand the full text of the null and alternative hypotheses presented in this section, the reader will have to read the protocol involved in conducting the **Moses test for equal variability**, which is described in Section IV.

Null hypothesis

$$H_0: \sigma_1^2 = \sigma_2^2$$

(The variance of the population Group 1 represents equals the variance of the population Group 2 represents. When, within the framework of the **Mann–Whitney *U* test** analysis to be described, both groups have an equal sample size, this translates into the sum of the ranks of the sums of the squared difference scores of Group 1 being equal to the sum of the ranks of the sums of the squared difference scores of Group 2. A more general way of stating this, which also encompasses designs involving unequal sample sizes, is that the means of the ranks of the sums of the squared difference scores of the two groups are equal.)

Alternative hypothesis

$$H_1: \sigma_1^2 \neq \sigma_2^2$$

(The variance of the population Group 1 represents does not equal the variance of the population Group 2 represents. When, within the framework of the **Mann–Whitney *U* test** analysis to be described, both groups have an equal sample size, this translates into the sum of the ranks of the sums of the squared difference scores of Group 1 not being equal to the sum of the ranks of the sums of the squared difference scores of Group 2. A more general way of stating this, which also encompasses designs involving unequal sample sizes, is that the means of the ranks of the sums of the squared difference scores of the two groups are not equal. This is a **nondirectional alternative hypothesis** and it is evaluated with a **two-tailed test**.)

or

$$H_1: \sigma_1^2 > \sigma_2^2$$

(The variance of the population Group 1 represents is greater than the variance of the population Group 2 represents. When, within the framework of the **Mann–Whitney *U* test** analysis to be described, both groups have an equal sample size (so long as a rank of 1 is given to the lowest score), this translates into the sum of the ranks of the sums of the squared difference scores of Group 1 being greater than the sum of the ranks of the sums of the squared difference scores of Group 2. A more general way of stating this, which also encompasses designs involving unequal sample sizes, is that the mean of the ranks of the sums of the squared difference scores of Group 1 is greater than the mean of the ranks of the sums of the squared difference scores of Group 2. This is a **directional alternative hypothesis** and it is evaluated with a **one-tailed test**.)

or

$$H_1: \sigma_1^2 < \sigma_2^2$$

(The variance of the population Group 1 represents is less than the variance of the population Group 2 represents. When, within the framework of the **Mann–Whitney *U* test** analysis to be described, both groups have an equal sample size (so long as a rank of 1 is given to the lowest score), this translates into the sum of the ranks of the sums of the squared difference scores of Group 1 being less than the sum of the ranks of the sums of the squared difference scores of Group 2. A more general way of stating this, which also encompasses designs involving unequal sample sizes, is that the mean of the ranks of the sums of the squared difference scores of Group 1 is less than the mean of the ranks of the sums of the squared difference scores of Group 2. This is a **directional alternative hypothesis** and it is evaluated with a **one-tailed test**.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis is rejected.

IV. Test Computations

The protocol described below is employed for computing the test statistic for the **Moses test for equal variability**. In employing the protocol the following values are applicable: a) The total number of subjects employed in the experiment is $N = 12$; and b) There are $n_1 = 6$ subjects in Group 1 and $n_2 = 6$ subjects in Group 2.

a) The protocol for the **Moses test for equal variability** requires that the original interval/ratio scores be broken down into subsamples. A subsample is a set of scores derived from a sample, with the number of scores in a subsample being less than the total number of scores in the sample.

b) Divide the n_1 scores in Group 1 into m_1 subsamples (where $m_1 > 1$), with each subsample being comprised of k scores. Selection of the k scores for each of the m_1 subsamples should be random. **Sampling without replacement** (which is defined in Endnote 1 of the **binomial sign test for a single sample (Test 9)**) is employed in forming the subsamples. In other words, each of the n_1 scores in Group 1 is employed in only one of the m_1 subsamples.

c) Divide the n_2 scores in Group 2 into m_2 subsamples (where $m_2 > 1$), with each subsample being comprised of k scores. Selection of the k scores for each of the m_2 subsamples should be random. **Sampling without replacement** is employed in forming the subsamples. In other words, each of the n_2 scores in Group 2 is employed in only one of the m_2 subsamples.¹

d) Note that regardless of which group a subsample is derived from, all subsamples will be comprised of the same number of scores (i.e., k scores). The number of subsamples derived from each group, however, need not be equal. In other words, the values of m_1 and m_2 do not have to be equivalent. The number of scores in each subsample should be such that the products $(m_1)(k)$ and $(m_2)(k)$ include as many of the scores as possible. Although the optimal situation would be if $(m_1)(k) = n_1$ and $(m_2)(k) = n_2$, it will often not be possible to achieve the latter (i.e., include all N scores in the $m_1 + m_2$ subsamples).

To illustrate the formation of subsamples, let us assume that $n_1 = 20$ and $n_2 = 20$. Employing the data from Group 1, we can form $m_1 = 4$ subsamples comprised of $k = 5$ scores per subsample. Thus, each of the $n_1 = 20$ scores in Group 1 will be included in one of the subsamples. Employing the data from Group 2, we can form $m_2 = 4$ subsamples comprised of $k = 5$ scores per subsample. Thus, each of the $n_2 = 20$ scores in Group 2 will be included in one of the subsamples. Now let us assume that in Group 1 there are only 18 subjects (i.e., $n_1 = 18$ and $n_2 = 20$). If we still employ $k = 5$ scores per subsample, we can only form $m_1 = 3$ subsamples (which includes 15 of the 18 scores in Group 1). In such a case, three scores in Group 1 will have to be omitted from the analysis (which will employ $m_1 = 3$ subsamples comprised of $k = 5$ scores per subsample, and $m_2 = 4$ subsamples comprised of $k = 5$ scores per subsample). In order to include more subjects in the total analysis with $n_1 = 18$ and $n_2 = 20$, we can employ $k = 4$ scores per subsample, in which case we will have $m_1 = 4$ subsamples comprised of $k = 4$ scores per subsample, and $m_2 = 5$ subsamples comprised of $k = 4$ scores per subsample. In the latter case, only two scores in Group 1 will have to be omitted from the analysis. Obviously, if $n_1 = 18$ and $n_2 = 20$, we can only include all $N = 20$ subjects in the analysis, if we have $k = 2$ scores per subsample. In such a case we will have $m_1 = 9$ subsamples comprised of $k = 2$ scores per subsample, and $m_2 = 10$ subsamples comprised of $k = 2$ scores per subsample.

Daniel (1990) notes that Shorack (1969) recommends the following criteria in determining the values of k , m_1 , and m_2 : 1) k should be as large as possible, but not more than 10; and 2) The values of m_1 and m_2 should be large enough to derive meaningful results. The latter translates into employing values for m_1 and m_2 that meet the minimum sample size requirements for the

Mann–Whitney *U* test, which is employed to compute the test statistic for the **Moses test for equal variability**. This latter point will be clarified in Section V.

d) Compute the mean of each of the m_1 subsamples derived from Group 1. Within each subsample do the following: 1) Subtract the mean of the subsample from each of the k scores in the subsample; 2) Square each of the difference scores; and 3) Obtain the sum of the k squared difference scores. The notation $\sum D_{1i}^2$ will represent the sum of the squared difference scores for the i^{th} subsample in Group 1. There will be a total of $m_1 \sum D_{1i}^2$ scores for Group 1.

e) Compute the mean of each of the m_2 subsamples derived from Group 2. Within each subsample do the following: 1) Subtract the mean of the subsample from each of the k scores in the subsample; 2) Square each of the difference scores; and 3) Obtain the sum of the k squared difference scores. The notation $\sum D_{2i}^2$ will represent the sum of the squared difference scores for the i^{th} subsample in Group 2. There will be a total of $m_2 \sum D_{2i}^2$ scores for Group 2.

f) The reader may want to review the protocol for the **Mann–Whitney *U* test** (in Section IV of the latter test) prior to continuing this section, since at this point in the analysis the **Mann–Whitney *U* test** is employed to compute the test statistic for the **Moses test for equal variability**. Specifically, within the framework of the **Mann–Whitney *U* test** model, each of the m_1 sums of the squared difference scores in Group 1 (i.e., the $m_1 \sum D_{1i}^2$ scores) is conceptualized as one of the n_1 scores in Group 1, and each of the m_2 sums of the squared difference scores in Group 2 (i.e., the $m_2 \sum D_{2i}^2$ scores) is conceptualized as one of the n_2 scores in Group 2.

If the null hypothesis is true, it is expected that the rank orders for the sums of the squared difference scores in Groups 1 and 2 will be evenly dispersed and, consequently, the sum of the ranks for the Group 1 $\sum D_{1i}^2$ scores will be equal or close to the sum of the ranks for the Group 2 $\sum D_{2i}^2$ scores. If, on the other hand, there is greater variability in one of the groups, the rank-orderings of the sums of the squared difference scores for that group will be higher than the rank-orderings of the sums of the squared difference scores for the other group.

The protocol described in this section for the **Moses test for equal variability** will now be employed to evaluate Example 15.1. Table 15.1 summarizes the initial part of the analysis, which requires that subsamples be selected from each of the groups. As a result of the small sample size employed in the study, each subsample will be comprised of $k = 2$ scores, and thus there will be $m_1 = 3$ subsamples for Group 1 and $m_2 = 3$ subsamples for Group 2. Since $(m_1)(k) = (3)(2) = 6 = n_1$ and $(m_2)(k) = (3)(2) = 6 = n_2$, the scores of all $N = 12$ subjects are employed in the analysis. As noted earlier, the assignment of scores to subsamples is random. In this instance the author used a table of random numbers to select the scores for each of the subsamples.²

Table 15.1 Summary of Analysis of Example 15.1

Group 1				
Subsample	\bar{X}	$(X - \bar{X})$	$(X - \bar{X})^2$	$\sum(X - \bar{X})^2 = \sum D_{1i}^2$
1) 1, 10	5.5	−4.5, 4.5	20.25, 20.25	40.5
2) 10, 0	5	5, −5	25, 25	50
3) 9, 0	4.5	4.5, −4.5	20.25, 20.25	40.5
Group 2				
Subsample	\bar{X}	$(X - \bar{X})$	$(X - \bar{X})^2$	$\sum(X - \bar{X})^2 = \sum D_{2i}^2$
1) 4, 4	4	0, 0	0, 0	0
2) 5, 6	5.5	−.5, .5	.25, .25	.5
3) 5, 6	5.5	−.5, .5	.25, .25	.5

15.2 Analysis of Example 15.1 with Mann–Whitney U Test

Group 1		Group 2	
ΣD_{1i}^2	Rank	ΣD_{2i}^2	Rank
40.5	4.5	0	1
50	6	.5	2.5
40.5	4.5	.5	2.5
$\Sigma R_1 = 15$		$\Sigma R_2 = 6$	
$U_1 = n_1 n_2 + \frac{n_1(n_1 + 1)}{2} - \Sigma R_1 = (3)(3) + \frac{3(3 + 1)}{2} - 15 = 0$			
$U_2 = n_1 n_2 + \frac{n_2(n_2 + 1)}{2} - \Sigma R_2 = (3)(3) + \frac{3(3 + 1)}{2} - 6 = 9$			

The information in [Table 15.1](#) can be summarized as follows: a) Column 1 lists the two scores in each subsample. Each row contains a separate subsample; b) Column 2 lists the mean (\bar{X}) of each subsample; c) Column 3 lists the difference scores $((X - \bar{X}))$ obtained when the mean of a subsample is subtracted from each score in the subsample; d) Column 4 lists the squared difference scores $((X - \bar{X})^2)$ for each subsample (which are the squares of the scores in Column 3); and e) Column 5 lists the sum of the squared difference scores ($\Sigma(X - \bar{X})^2 = \Sigma D_{ji}^2$) for each of the subsamples (i.e., within each row/subsample, the values in Column 5 are the sum of the values in Column 4). Note that the notation ΣD_{ji}^2 represents the sum of the squared difference scores of the i^{th} subsample in Group j . The values in Column 5 are evaluated in [Table 15.2](#) with the **Mann–Whitney U test**.

V. Interpretation of the Test Results

The smaller of the two values U_1 versus U_2 is designated as the obtained U statistic. Since $U_1 = 0$ is smaller than $U_2 = 9$, the value of $U = 0$. The value of U is evaluated with [Table A11 \(Table of Critical Values for the Mann–Whitney \$U\$ Statistic\)](#) in the **Appendix**.³ In the case of Example 15.1, there are three scores in each group (which are the sums of the squared difference scores for the three subsamples that comprise that group). Thus, $n_1 = 3$ and $n_2 = 3$. Because of the small sample size, [Table A11](#) does not list critical two-tailed .05 and .01 values, nor does it list a critical one-tailed .01 value. It does, however list the critical one-tailed .05 value $U_{.05} = 0$. In order to be significant, the obtained value of U must be **equal to or less than** the tabled critical value at the prespecified level of significance. Since $U = 0$ is equal to $U_{.05} = 0$, the directional alternative hypothesis that is consistent with the data is supported at the .05 level. The latter alternative hypothesis is $H_1: \sigma_1^2 > \sigma_2^2$.

In Section III it is noted that when both groups have an equal sample size, if the directional alternative $H_1: \sigma_1^2 > \sigma_2^2$ is supported, the sum/average of the ranks of the sums of the squared difference scores of Group 1 will be greater than the sum/average of the ranks of the sums of the squared difference scores of Group 2 (i.e., $\Sigma R_1 > \Sigma R_2$). Since the latter is the case in Example 15.1, the directional alternative hypothesis $H_1: \sigma_1^2 > \sigma_2^2$ is supported at the .05 level.

For the directional alternative hypothesis $H_1: \sigma_1^2 < \sigma_2^2$ to be supported, the sum/average of the ranks of the sums of the squared difference scores of Group 2 must be greater than the sum/ average of the ranks of the sums of the squared difference scores of Group 1 (i.e., $\Sigma R_1 < \Sigma R_2$). Since, as noted above, the opposite is true, the directional alternative hypothesis $H_1: \sigma_1^2 < \sigma_2^2$ is not supported.

For the nondirectional alternative hypothesis $H_1: \sigma_1^2 \neq \sigma_2^2$ to be supported, the sum/average of the ranks of the sums of the squared difference scores of Group 1 must not be equal to the sum/average of the ranks of the sums of the squared difference scores of Group 2 (i.e., $\Sigma R_1 \neq \Sigma R_2$). In point of fact, the latter is true, and the computed value $U = 0$ is the smallest possible U value that can be obtained. However, as noted earlier, because of the small sample size, no two-tailed .05 and .01 critical values are listed in [Table A11](#) for $n_1 = 3$ and $n_2 = 3$.

Based on the results of the **Moses test for equal variability**, the researcher can conclude that there is greater variability in the depression scores of the group that receives the drug Elatrix (Group 1) than the group that receives the drug Euphyria (Group 2).

When the same data are evaluated with the **Siegel–Tukey test for equal variability**, as well as with **Hartley's F_{\max} test for homogeneity of variance/F test for two population variances**, both the nondirectional alternative hypothesis $H_1: \sigma_1^2 \neq \sigma_2^2$ and the directional alternative hypothesis $H_1: \sigma_1^2 > \sigma_2^2$ are supported at both the .05 and .01 levels. The fact that the latter two alternative procedures for evaluating the null hypothesis $H_0: \sigma_1^2 = \sigma_2^2$ yield a more significant result than the **Moses test** is consistent with the fact that of the three procedures, the one with the lowest statistical power is the **Moses test** (the issue of the power of the **Moses test for equal variability** is discussed in greater detail in Section VII).

VI. Additional Analytical Procedures for the Moses Test for Equal Variability and/or Related Tests

1. The normal approximation of the Moses test statistic for large sample sizes Although the sample size is too small to employ the large sample normal approximation of the **Mann–Whitney U test** statistic, for demonstration purposes the latter value is computed below with Equation 12.4. As is noted in Section VI of the **Mann–Whitney U test**, the large sample normal approximation is generally used for sample sizes larger than those documented in the exact table for the **Mann–Whitney U test** contained within the source one is employing. Employing Equation 12.4, the absolute value $z = 1.96$ is computed.

The obtained absolute value $z = 1.96$ is evaluated with [Table A1 \(Table of the Normal Distribution\)](#) in the **Appendix**. In order to be significant, the obtained absolute value of z must be equal to or greater than the tabled critical value at the prespecified level of significance. The tabled critical two-tailed .05 and .01 values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed .05 and .01 values are $z_{.05} = 1.65$ and $z_{.01} = 2.33$.

$$z = \frac{U - \frac{n_1 n_2}{2}}{\sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12}}} = \frac{0 - \frac{(3)(3)}{2}}{\sqrt{\frac{(3)(3)(3 + 3 + 1)}{12}}} = -1.96$$

The following guidelines are employed in evaluating the null hypothesis.

a) If the nondirectional alternative hypothesis $H_1: \sigma_1^2 \neq \sigma_2^2$ is employed, the null hypothesis can be rejected if the obtained absolute value of z is equal to or greater than the tabled critical two-tailed value at the prespecified level of significance.

b) If a directional alternative hypothesis is employed, one of the two possible directional alternative hypotheses is supported if the obtained absolute value of z is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance. The directional alternative hypothesis that is supported is the one that is consistent with the data.

Since the computed absolute value $z = 1.96$ is equal to $z_{.05} = 1.96$ but less than

$z_{.01} = 2.58$, the nondirectional alternative hypothesis $H_1: \sigma_1^2 \neq \sigma_2^2$ is supported at the .05 level, but not at the .01 level. Since the computed absolute value $z = 1.96$ is greater than $z_{.05} = 1.65$ but less than $z_{.01} = 2.33$, the directional alternative hypothesis $H_1: \sigma_1^2 > \sigma_2^2$ is supported at the .05 level, but not at the .01 level.

The continuity-corrected Equation 12.5 yields the slightly lower absolute value $z = 1.75$. Since the computed absolute value $z = 1.75$ is greater than $z_{.05} = 1.65$ but less than $z_{.01} = 2.33$, the directional alternative hypothesis $H_1: \sigma_1^2 > \sigma_2^2$ is supported, but only at the .05 level. Since the computed absolute value $z = 1.75$ is less than $z_{.05} = 1.96$ and $z_{.01} = 2.58$, the nondirectional alternative hypothesis $H_1: \sigma_1^2 \neq \sigma_2^2$ is not supported. Thus, the result obtained with the continuity-corrected equation is exactly the same as the result obtained when the values in [Table A11](#) are employed.

$$z = \frac{\left| U - \frac{n_1 n_2}{2} \right| - .5}{\sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12}}} = \frac{\left| 0 - \frac{(3)(3)}{2} \right| - .5}{\sqrt{\frac{(3)(3)(3 + 3 + 1)}{12}}} = -1.75$$

VII. Additional Discussion of the Moses Test for Equal Variability

1. Power-efficiency of the Moses test for equal variability Daniel (1990) and Siegel and Castellan (1988) note that the power-efficiency of the **Moses test for equal variability** relative to a parametric procedure such as **Hartley's F_{\max} test for homogeneity of variance/ F test for two population variances** is a function of the size of the subsamples. With small subsamples the **asymptotic relative efficiency** (which is discussed in Section VII of the **Wilcoxon signed-ranks test**) of the test is relatively low if the underlying population distributions are normal (e.g., the power efficiency is .50 when $k = 3$). Although as the value of k increases, the power efficiency approaches an upper limit of .95, the downside of employing a large number of scores in each subsample is that as k increases, the number of subsamples that are available for analysis will decrease (and the latter will compromise the power of the **Mann-Whitney** analysis employed to compute the **Moses test** statistic). Thus, in deciding whether to employ the **Moses test for equal variability**, the researcher must weigh the test's relatively low power efficiency against the following factors: a) The extreme sensitivity of **Hartley's F_{\max} test for homogeneity of variance/ F test for two population variances** to violations of the assumption of normality in the underlying populations (which is not an assumption of the **Moses test**); and b) The assumption of equal population medians associated with the **Siegel-Tukey test for equal variability**. Since the power of a statistical test is directly related to sample size, for the same set of data, the **Siegel-Tukey test for equal variability** will have higher power than the **Moses test for equal variability**. The latter is true, since the sample size for the test statistic with the **Siegel-Tukey test** will always be the values n_1 and n_2 , while with the **Moses test** the sample size will be m_1 and m_2 (the values of which will always be less than n_1 and n_2).

2. Issue of repetitive resampling An obvious problem associated with the **Moses test for equal variability** is that its result is dependent on the configuration of the data in each of the random subsamples employed in the analysis. It is entirely possible that an analysis based on one set of subsamples may yield a different result than an analysis based on a different set of subsamples. Because of the latter, if a researcher has a bias in favor of obtaining a significant (or perhaps nonsignificant) result, she can continue to select subsamples until she obtains a set of

subsamples that yields the desired result. Obviously, the latter protocol is inappropriate and would compromise the integrity of one's results. Put simply, the **Moses test for equal variability** should be run one time, with the researcher accepting the resulting outcome. If the researcher has reason to believe the outcome does not reflect the truth regarding the populations in question, a replication study should be conducted.

3. Alternative nonparametric tests of dispersion In Section I it is noted that the **Moses test for equal variability** is one of a number of nonparametric tests that have been developed for evaluating the hypothesis that two populations have equal variances. The determination with respect to which of these tests to employ is generally based on the specific assumptions a researcher is willing to make about the underlying population distributions. Other factors that can determine which test a researcher elects to employ are the relative power efficiencies of the tests under consideration, and the complexity of the computations required for a specific test. As noted in Section VI of the **Siegel–Tukey test for equal variability**, among the other procedures that are available for evaluating a hypothesis about equality of population variances are the **Ansari–Bradley test** (Ansari and Bradley (1960) and Freund and Ansari (1957)), and nonparametric tests of dispersion developed by Conover (Conover and Iman (1978), Conover (1980, 1999)), Hollander (1963), Klotz (1962), Mood (1954), and Moses (1952). Of the aforementioned tests, the **Siegel–Tukey test for equal variability**, the **Klotz test**, and the **Mood test** can be extended to designs involving more than two independent samples.

Since there is extensive literature on nonparametric tests of dispersion, the interested reader should consult sources that specialize in nonparametric statistics for a more comprehensive discussion of the subject. One or more of these procedures are described in detail in various books that specialize in nonparametric statistics (e.g., Conover (1980, 1999), Daniel (1990), Hollander and Wolfe (1999), Marascuilo and McSweeney (1977), Siegel and Castellan (1988), and Sprent (1993)). In addition, Sheskin (1984) provides a general overview and bibliography of nonparametric tests of dispersion.

VIII. Additional Examples Illustrating the Moses Test for Equal Variability

In the discussion of the **Siegel–Tukey test for equal variability**, Example 14.2 was employed to illustrate an example in which a researcher is not able to assume that the two population medians are equal. Although the latter is a situation where the **Moses test for equal variability** would be more appropriate to employ than the **Siegel–Tukey test** (since the **Moses test** doesn't assume equal population medians), because of the small sample size ($n_1 = 5$ and $n_2 = 6$) the **Moses test** cannot be employed. In the case of Example 14.2, the only way to obtain more than one subsample per group is to set $k = 2$, and have $m_1 = 2$ subsamples in Group 1 (for which the five scores are 7, 5, 4, 4, 3), and $m_2 = 3$ subsamples in Group 2 (for which the six scores are 13, 12, 7, 7, 4, 3). However, since there are no critical values listed in the **Mann–Whitney** table (i.e., **Table A11**) for $n_1 = 2$ and $n_2 = 3$ (which are the number of subsamples/sums of squared difference scores in each group), the probability level associated with the result of the **Mann–Whitney U test** will always be above .05, regardless of whether a one-tailed or two-tailed analysis is employed.

Example 15.2 is an additional problem that will be evaluated with the **Moses test for equal variability**.

Example 15.2 *A researcher wants to determine whether or not a group of subjects who are given a low dose of a stimulant drug exhibit more variability with respect to the number of errors*

they make on a test of eye-hand coordination than a group of subjects who are given a placebo. There are $n_1 = 12$ subjects in the group administered the drug and $n_2 = 17$ subjects in the placebo group. The scores of the $N = 29$ subjects are listed below.

Group 1: 8, 5, 4, 3, 2, 9, 6, 1, 14, 18, 8, 8

Group 2: 7, 7, 7, 8, 9, 7, 8, 9, 8, 8, 7, 10, 11, 12, 7, 9, 5

Is there a significant difference between the degree of variability within each of the groups?

In evaluating the data with the **Moses test for equal variability** we will employ $k = 3$ subjects per subsample, which means that we will derive $m_1 = 4$ subsamples for Group 1 (since $n_1 = 12$ divided by 3 equals 4), and $m_2 = 5$ subsamples for Group 1 (since $n_2 = 17$ divided by 3 equals 5, with a remainder of 2). Since $n_2 = 17$ is not evenly divisible by 3, two of the scores in Group 2 will not be included in the Group 2 subsamples (specifically, the score of one of the six subjects who obtained a 7 and the score of the subject who obtained a 5 were not selected for inclusion in the Group 2 subsamples during the random selection process). [Tables 15.3](#) and [15.4](#) summarize the analysis. In [Table 15.4](#), within the framework of the **Mann-Whitney U test**, the values $n_1 = 4$ and $n_2 = 5$ are employed to represent the $m_1 = 4$ sums of squared difference scores for Group 1 and the $m_2 = 5$ sums of squared difference scores for Group 2.

Table 15.3 Summary of Analysis of Example 15.2

Group 1				
Subsample	\bar{X}	$(X - \bar{X})$	$(X - \bar{X})^2$	$\Sigma(X - \bar{X})^2 = \Sigma D_{1i}^2$
1) 5, 6, 4	5	0, 1, -1	0, 1, 1	2
2) 8, 18, 1	9	-1, 9, -8	1, 81, 64	146
3) 8, 14, 9	10.33	-2.33, 3.67, -1.33	5.43, 13.47, 1.77	20.67
4) 3, 8, 2	4.33	-1.33, 3.67, -2.33	1.77, 13.47, 5.43	20.67
Group 2				
Subsample	\bar{X}	$(X - \bar{X})$	$(X - \bar{X})^2$	$\Sigma(X - \bar{X})^2 = \Sigma D_{2i}^2$
1) 12, 7, 7	8.67	3.33, -1.67, -1.67	11.09, 2.79, 2.79	16.67
2) 9, 9, 8	8.67	.33, .33, -.67	.11, .11, .45	.67
3) 10, 11, 7	9.33	.67, 1.67, -2.33	.45, 2.79, 5.43	8.67
4) 8, 8, 7	7.67	.33, .33, -.67	.11, .11, .45	.67
5) 8, 7, 9	8	0, -1, 1	0, 1, 1	2

Since $U_1 = 2.5$ is smaller than $U_2 = 17.5$, the value of $U = 2.5$. Employing [Table A11](#), for the values $n_1 = 4$ and $n_2 = 5$, the tabled critical two-tailed .05 value is $U_{.05} = 1$. Because of the small sample size, no tabled critical two-tailed .01 value is listed. The tabled critical one-tailed values are $U_{.05} = 2$ and $U_{.01} = 0$. Since the computed value $U_1 = 2.5$ is larger than all of the tabled critical values, the null hypothesis cannot be rejected, regardless of which alternative hypothesis is employed. Thus, the researcher cannot conclude that there are differences in the variances of the two groups.

The data for Example 15.2 are consistent with the directional alternative hypothesis $H_1: \sigma_1^2 > \sigma_2^2$, since the average of the ranks for Group 1 ($\bar{R}_1 = 6.875$) is larger than the average of the ranks for Group 2 ($\bar{R}_2 = 3.5$). Support for the latter directional alternative hypothesis falls just short of being significant, since $U = 2.5$ is only .5 units above the tabled critical one-tailed value $U_{.05} = 2$.

15.4 Analysis of Example 15.2 with Mann–Whitney U Test

Group 1		Group 2	
ΣD_{1i}^2	Rank	ΣD_{2i}^2	Rank
2	3.5	16.67	6
146	9	.67	1.5
20.67	7.5	8.67	5
20.67	7.5	.67	1.5
		2	3.5
$\Sigma R_1 = 27.5$		$\Sigma R_2 = 17.5$	
$U_1 = n_1 n_2 + \frac{n_1(n_1 + 1)}{2} - \Sigma R_1 = (4)(5) + \frac{4(4 + 1)}{2} - 27.5 = 2.5$			
$U_2 = n_1 n_2 + \frac{n_2(n_2 + 1)}{2} - \Sigma R_2 = (4)(5) + \frac{5(5 + 1)}{2} - 17.5 = 17.5$			

15.5 Analysis of Example 15.2 with Siegel–Tukey Test for Equal Variability

Group 1		Group 2	
ΣD_{1i}^2	Rank	ΣD_{2i}^2	Rank
8	24.86	7	20.5
5	10.5	7	20.5
4	8	7	20.5
3	5	8	24.86
2	4	9	14.5
9	14.5	7	20.5
6	13	8	24.86
1	1	9	14.5
14	3	8	24.86
18	2	8	24.86
8	24.86	7	20.5
8	24.86	10	10
		11	7
		12	6
		7	20.5
		9	14.5
		5	10.5
$\Sigma R_1 = 135.58$		$\Sigma R_2 = 299.44$	
$U_1 = n_1 n_2 + \frac{n_1(n_1 + 1)}{2} - \Sigma R_1 = (12)(17) + \frac{12(12 + 1)}{2} - 135.58 = 146.42$			
$U_2 = n_1 n_2 + \frac{n_2(n_2 + 1)}{2} - \Sigma R_2 = (12)(17) + \frac{17(17 + 1)}{2} - 299.44 = 57.56$			

It turns out that when the data for Example 15.2 are evaluated with the **Siegel–Tukey test for equal variability**, the computed value of the test statistic (through use of the **Mann–Whitney U test**) is $U = 57.56$.⁴ [Table 15.5](#) summarizes the analysis with the **Siegel–Tukey test**. In the case of the **Siegel–Tukey test**, the original sample size values $n_1 = 12$ and $n_2 = 17$ are employed in obtaining critical values from [Table A11](#). For $n_1 = 12$ and $n_2 = 17$, the tabled critical two-tailed .05 and .01 values are $U_{.05} = 57$ and $U_{.01} = 44$, and the tabled critical one-tailed .05 and .01

values are $U_{.05} = 64$ and $U_{.01} = 49$. Since $U = 57.56$ is greater (albeit barely) than the tabled critical two-tailed value $U_{.05} = 57$, the nondirectional alternative hypothesis $H_1: \sigma_1^2 \neq \sigma_2^2$ is not supported. The directional alternative hypothesis $H_1: \sigma_1^2 > \sigma_2^2$ is supported, but only at the .05 level, since $U = 57.56$ is less than the tabled critical one-tailed value $U_{.05} = 64$. Thus, when the **Siegel–Tukey test for equal variability** is employed, the researcher can conclude that there is greater variability in the scores of Group 1.

When the data for Example 15.2 are evaluated with **Hartley's F_{\max} test for homogeneity of variance/ F test for two population variances**, the nondirectional alternative hypothesis $H_1: \sigma_1^2 \neq \sigma_2^2$ and the directional alternative hypothesis $H_1: \sigma_1^2 > \sigma_2^2$ are supported at both the .05 and .01 levels. The computations for the latter test are shown below. Equation 11.6 is employed to compute the value $F_{\max} = 8.39$.

$$\begin{aligned}\hat{s}_1^2 &= \frac{\Sigma X_1^2 - \frac{(\Sigma X_1)^2}{n_1}}{n_1 - 1} = \frac{884 - \frac{(86)^2}{12}}{12 - 1} = 24.33 \\ \hat{s}_2^2 &= \frac{\Sigma X_2^2 - \frac{(\Sigma X_2)^2}{n_2}}{n_2 - 1} = \frac{1183 - \frac{(139)^2}{17}}{17 - 1} = 2.90 \\ F_{\max} &= \frac{\hat{s}_L^2}{\hat{s}_S^2} = \frac{24.33}{2.90} = 8.39\end{aligned}$$

The computed value $F_{\max} = 8.39$ is evaluated with **Table A9 (Table of the F_{\max} Distribution)** in the **Appendix**. The tabled critical values for the F_{\max} distribution are listed in reference to the values $(n - 1)$ and k , where n represents the number of subjects per group, and k represents the number of groups. In the case of Example 15.2, the computed value $F_{\max} = 8.39$ is larger than the tabled critical values in **Table A9** for $k = 2$ and $n = 12$. (With unequal sample sizes, for the most conservative test of the null hypothesis, we employ the smaller of the two sample size values $n_1 = 12$ and $n_2 = 17$.)⁵ The tabled critical values for $k = 2$ and $n = 12$ are $F_{\max_{.05}} = 3.28$ and $F_{\max_{.01}} = 4.91$. Since the obtained value $F_{\max} = 8.39$ is larger than both of the aforementioned critical values, we can reject the null hypothesis at both the .05 and .01 level. Thus, the nondirectional alternative hypothesis $H_1: \sigma_1^2 \neq \sigma_2^2$ is supported. If the latter nondirectional alternative hypothesis is supported at both the .05 and .01 levels, the directional alternative hypothesis $H_1: \sigma_1^2 > \sigma_2^2$ will also be supported at both .05 and .01 levels, since the critical values for the latter alternative hypothesis will be lower than the critical two-tailed values noted above. Thus, when **Hartley's F_{\max} test for homogeneity of variance/ F test for two population variances** is employed, the researcher can conclude that there is a higher degree of variability in the scores of Group 1. As noted earlier, the latter test will generally provide a more powerful test of an alternative hypothesis than either the **Moses test** (which does not yield a significant result for Example 15.2) or the **Siegel–Tukey test** (which does yield a significant result for Example 15.2, but only for a one-tailed alternative hypothesis).

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Endnotes

1. One could argue that the use of random subsamples for the **Moses test for equal variability** allows one to conceptualize the test within the framework of the general category of re-sampling procedures, which are discussed in Section IX (the **Addendum**) of the **Mann–Whitney U test**.
2. A typical table of random numbers is a computer generated series of random digits that fall within the range 0 through 9. If there are six scores in a group, the sequential appearance of the digits 1 through 6 in the table can be used to form subsamples. For example, let us assume that the following string of digits appears in a random number table: 2352239455675900912937373949404. We will form three subsamples, with two scores per subsample. Since the first digit that appears in the random number table is 2, the second score listed for the group will be the first score assigned to a Subsample 1. Since 3 is the next digit, the third score listed becomes the second score in Subsample 1. Since 5 is the next digit, the fifth score listed becomes the first score in the Subsample 2. We ignore the next four digits

(2, 2, 3 and 9) since: a) We have already selected the second and third scores from the group; and b) The digit 9 indicates that we should select the ninth score. The latter score, however, does not exist, since there are only six scores in the group. Since the next digit is 4, the fourth score in the group becomes the second score in the Subsample 2. By default, the two scores that remain in the group (the first and sixth scores) will comprise Subsample 3.

3. The large sample normal approximation for the **Mann–Whitney U test** (i.e., Equations 12.4 or 12.5) can be employed when the values of m_1 and m_2 used to represent n_1 and n_2 are such that one or both of the values is larger than the largest tabled value in [Table A11](#). Equation 12.6 (the tie-corrected **Mann–Whitney** normal approximation equation) can be employed if ties are present in the data (i.e., there are one or more identical values for squared difference score sums).
4. For purposes of illustration we will assume that the medians of the populations the two groups represent are equal (which is an assumption of the **Siegel–Tukey test for equal variability**). In actuality, the sample medians computed for Groups 1 and 2 are respectively 7 and 8.
5. When $n_1 \neq n_2$, the smaller sample size is employed when using [Table A9](#) in order to minimize the likelihood of committing a Type I error.

Test 16

The Chi-Square Test for $r \times c$ Tables (Nonparametric Test Employed with Categorical/Nominal Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test In the underlying population(s) represented by the sample(s) in a contingency table, are the observed cell frequencies different from the expected frequencies?

Relevant background information on test The **chi-square test for $r \times c$ tables** is one of a number of tests described in this book for which the chi-square distribution is the appropriate sampling distribution.¹ The **chi-square test for $r \times c$ tables** is an extension of the **chi-square goodness-of-fit test (Test 8)** to two-dimensional tables. Whereas the latter test can only be employed with a single sample categorized on a single dimension (the single dimension is represented by the k cells/categories that comprise the frequency distribution table), the **chi-square test for $r \times c$ tables** can be employed to evaluate designs that summarize categorical data in the form of an $r \times c$ table (which is often referred to as a **contingency table**). An $r \times c$ table consists of r rows and c columns. Both the values of r and c are integer numbers that are equal to or greater than 2. The total number of cells in an $r \times c$ table is obtained by multiplying the value of r by the value of c . The data contained in each of the cells of a contingency table represent the number of observations (i.e., subjects or objects) that are categorized in the cell.

Table 16.1 presents the general model for an $r \times c$ contingency table. There are a total of n observations in the table. Note that each cell is identified with a subscript that consists of two elements. The first element identifies the row in which the cell falls and the second element identifies the column in which the cell falls. Thus, the notation O_{ij} represents the number of observations in the cell that is in the i^{th} row and the j^{th} column. $O_{i.}$ represents the number of observations in the i^{th} row and $O_{.j}$ represents the number of observations in the j^{th} column.

Table 16.1 General Model for an $r \times c$ Contingency Table

		Column variable						Row sums
		C_1	C_2	...	C_j	...	C_c	
Row variable	R_1	O_{11}	O_{12}	...	O_{1j}	...	O_{1c}	$O_{1.}$
	R_2	O_{21}	O_{22}	...	O_{2j}	...	O_{2c}	$O_{2.}$
	\vdots	\vdots	\vdots		\vdots		\vdots	\vdots
	R_i	O_{i1}	O_{i2}	...	O_{ij}	...	O_{ic}	$O_{i.}$
	\vdots	\vdots	\vdots		\vdots		\vdots	\vdots
	R_r	O_{r1}	O_{r2}	...	O_{rj}	...	O_{rc}	$O_{r.}$
Column sums		$O_{.1}$	$O_{.2}$...	$O_{.j}$...	$O_{.c}$	n

In actuality, there are two chi-square tests that can be conducted with an $r \times c$ table. The two tests that will be described are the **chi-square test for homogeneity (Test 16a)** and the **chi-square test of independence (Test 16b)**. The general label **chi-square test for $r \times c$ tables** will be employed to refer to both of the aforementioned tests, since the two tests are computationally identical. Although, in actuality, the **chi-square test for homogeneity** and the **chi-square test of independence** evaluate different hypotheses, a generic hypothesis can be stated that is applicable to both tests. A brief description of the two tests follows.

The chi-square test for homogeneity (Test 16a) The **chi-square test for homogeneity** is employed when r independent samples (where $r \geq 2$) are categorized on a single dimension which consists of c categories (where $c \geq 2$). The data for the r independent samples (which are generally represented by the r rows of the contingency table) are recorded with reference to the number of observations in each of the samples that fall within each of c categories (which are generally represented by the c columns of the contingency table). It is assumed that each of the samples is randomly drawn from the underlying population it represents. The **chi-square test for homogeneity** evaluates whether or not the r samples are homogeneous with respect to the proportion of observations in each of the c categories. To be more specific, if the data are homogeneous, the proportion of observations in the j^{th} category will be equal in all of the r populations. The **chi-square test for homogeneity** assumes that the sums of the r rows (which represent the number of observations in each of the r samples) are determined by the researcher prior to the data collection phase of a study. Example 16.1 in Section II is employed to illustrate the **chi-square test for homogeneity**.

The chi-square test of independence (Test 16b) The **chi-square test of independence** is employed when a single sample is categorized on two dimensions/variables. It is assumed that the sample is randomly selected from the population it represents. One of the dimensions/variables is comprised of r categories (where $r \geq 2$) that are represented by the r rows of the contingency table, while the second dimension/variable is comprised of c categories (where $c \geq 2$) that are represented by the c columns of the contingency table. The **chi-square test of independence** evaluates the general hypothesis that the two variables are independent of one another. Another way of stating that two variables are independent of one another is to say that there is a zero correlation between them. A zero correlation indicates there is no way to predict at above chance in which category an observation will fall on one of the variables, if it is known which category the observation falls on the second variable. (For an overview of the concept of correlation, the reader should consult Section I of the **Pearson product-moment correlation coefficient (Test 28)**.) The **chi-square test of independence** assumes that neither the sums of the r rows (which represent the number of observations in each of the r categories for Variable 1) or the sums of the c columns (which represent the number of observations in each of the c categories for Variable 2) are predetermined by the researcher prior to the data collection phase of a study. Example 16.2 in Section II is employed to illustrate the **chi-square test of independence**.

The **chi-square test for $r \times c$ tables** (i.e., both the **chi-square test for homogeneity** and the **chi-square test of independence**) is based on the following assumptions: a) Categorical/nominal data (i.e., frequencies) for $r \times c$ mutually exclusive categories are employed in the analysis; b) The data that are evaluated represent a random sample comprised of n independent observations. This assumption reflects the fact that each subject or object can only be represented once in the data; and c) The expected frequency of each cell in the contingency table is 5 or greater. When the expected frequency of one or more cells is less than 5, the probabilities in the chi-square distribution may not provide an accurate estimate of the underlying sampling distribution. As is the case for the **chi-square goodness-of-fit test**, sources are not in agreement with respect to the minimum acceptable value for an expected frequency. Many sources employ

criteria suggested by Cochran (1952), who stated that none of the expected frequencies should be less than 1, and that no more than 20% of the expected frequencies should be less than 5. However, many sources suggest the latter criteria may be overly conservative. In instances where a researcher believes that one or more expected cell frequencies are too small, two or more cells can be combined with one another to increase the values of the expected frequencies.

In actuality the chi-square distribution only provides an approximation of the exact sampling distribution for a contingency table.² The accuracy of the chi-square approximation increases as the size of the sample increases and, except for instances involving small sample sizes, the chi-square distribution provides an excellent approximation of the exact sampling distribution. One case for which an exact probability is often computed is a 2×2 contingency table involving a small sample size. In the latter instance, an exact probability can be computed through use of the hypergeometric distribution. The computation of an exact probability for a 2×2 table using the hypergeometric distribution is described under the **Fisher exact test (Test 16c)** in Section VI.

II. Examples

Example 16.1 *A researcher conducts a study in order to evaluate the effect of noise on altruistic behavior. Each of the 200 subjects who participate in the experiment is randomly assigned to one of two experimental conditions. Subjects in both conditions are given a one-hour test which is ostensibly a measure of intelligence. During the test the 100 subjects in Group 1 are exposed to continual loud noise, which they are told is due to a malfunctioning generator. The 100 subjects in Group 2 are not exposed to any noise during the test. Upon completion of this stage of the experiment, each subject on leaving the room is confronted by a middle-aged man whose arm is in a sling. The man asks the subject if she would be willing to help him carry a heavy package to his car. In actuality, the man requesting help is an experimental confederate (i.e., working for the experimenter). The number of subjects in each group who help the man is recorded. Thirty of the 100 subjects who were exposed to noise elect to help the man, while 60 of the 100 subjects who were not exposed to noise elect to help the man. Do the data indicate that altruistic behavior is influenced by noise?*

The data for Example 16.1, which can be summarized in the form of a 2×2 contingency table, are presented in Table 16.2.

Table 16.2 Summary of Data for Example 16.1				
	Helped the confederate	Did not help the confederate		Row sums
Noise	30	70		100
No noise	60	40		100
Column sums	90	110	Total observations	200

The appropriate test to employ for evaluating Example 16.1 is the **chi-square test for homogeneity**. This is the case, since the design of the study involves the use of categorical data (i.e., frequencies for each of the $r \times c$ cells in the contingency table) with multiple independent samples (specifically two) that are categorized on a single dimension (altruism). To be more specific, the differential treatments to which the two groups are exposed (i.e., **noise** versus **no-noise**) constitute the independent variable. The latter variable is the row variable, since it is represented by the two rows in Table 16.2. Note that the researcher assigns 100 subjects to each of the two levels of the independent variable prior to the data collection phase of the study. This

is consistent with the fact that when the **chi-square test for homogeneity** is employed, the sums for the row variable are predetermined prior to collecting the data. The dependent variable is whether or not a subject exhibits altruistic behavior. The latter variable is represented by the two categories **helped the confederate** versus **did not help the confederate**. The dependent variable is the column variable, since it is represented by the two columns in Table 16.2. The hypothesis that is evaluated with the **chi-square test for homogeneity** is whether there is a difference between the two groups with respect to the proportion of subjects who help the confederate.

Example 16.2 *A researcher wants to determine if there is a relationship between the personality dimension of introversion-extroversion and political affiliation. Two hundred people are recruited to participate in the study. All of the subjects are given a personality test on the basis of which each subject is classified as an introvert or an extrovert. Each subject is then asked to indicate whether he or she is a Democrat or a Republican. The data for Example 16.2, which can be summarized in the form of a 2×2 contingency table, are presented in Table 16.3. Do the data indicate there is a significant relationship between one's political affiliation and whether or not one is an introvert versus an extrovert?*

Table 16.3 Summary of Data for Example 16.2

	Democrat	Republican	Row sums
Introvert	30	70	100
Extrovert	60	40	100
Column sums	90	110	Total observations 200

The appropriate test to employ for evaluating Example 16.2 is the **chi-square test of independence**. This is the case since: a) The study involves a single sample that is categorized on two dimensions; and b) The data are comprised of frequencies for each of the $r \times c$ cells in the contingency table. To be more specific, a sample of 200 subjects is categorized on the following two dimensions, with each dimension being comprised of two mutually exclusive categories: a) **introvert** versus **extrovert**; and b) **Democrat** versus **Republican**. In Example 16.2 the **introvert-extrovert** dimension is the row variable and the **Democrat-Republican** dimension is the column variable.³ Note that in selecting the sample of 200 subjects, the researcher does not determine beforehand the number of **introverts**, **extroverts**, **Democrats**, and **Republicans** to include in the study.⁴ Thus, in Example 16.2 (consistent with the use of the **chi-square test of independence**) the sums of the rows and columns (which are referred to as the **marginal sums**) are not predetermined. The hypothesis that is evaluated with the **chi-square test of independence** is whether the two dimensions are independent of one another.

III. Null versus Alternative Hypotheses

Even though the hypotheses evaluated with the **chi-square test for homogeneity** and the **chi-square test of independence** are not identical, generic null and alternative hypotheses employing common symbolic notation can be used for both tests. The generic null and alternative hypotheses employ the observed and expected cell frequencies in the underlying population(s) represented by the sample(s). The observed and expected cell frequencies for the population(s) are represented respectively by the lower case Greek letters **omicron** (\omicron) and **epsilon** (ϵ). Thus, \omicron_{ij} and ϵ_{ij} respectively represent the observed and expected frequency of Cell _{ij} in the underlying population.

Null hypothesis

$$H_0: o_{ij} = \epsilon_{ij} \text{ for all cells}$$

(This notation indicates that in the underlying population(s) the sample(s) represent(s), for each of the $r \times c$ cells the observed frequency of a cell is equal to the expected frequency of the cell. With respect to the sample data, this translates into the observed frequency of each of the $r \times c$ cells being equal to the expected frequency of the cell.)

Alternative hypothesis

$$H_1: o_{ij} \neq \epsilon_{ij} \text{ for at least one cell}$$

(This notation indicates that in the underlying population(s) the sample(s) represent(s), for at least one of the $r \times c$ cells the observed frequency of a cell is not equal to the expected frequency of the cell. With respect to the sample data, this translates into the observed frequency of at least one of the $r \times c$ cells not being equal to the expected frequency of the cell. This notation should not be interpreted as meaning that in order to reject the null hypothesis there must be a discrepancy between the observed and expected frequencies for all $r \times c$ cells. Rejection of the null hypothesis can be the result of a discrepancy between the observed and expected frequencies for one cell, two cells, ..., or all $r \times c$ cells.)

Although it is possible to employ a directional alternative hypothesis for the **chi-square test for $r \times c$ tables**, in the examples used to describe the test it will be assumed that the alternative hypothesis will always be stated nondirectionally. A discussion of the use of a directional alternative hypothesis can be found in Section VI.

The null and alternative hypotheses for each of the two tests that are described under the **chi-square test for $r \times c$ tables** can also be expressed within the framework of a different format. The alternative format for stating the null and alternative hypotheses employs the proportion of observations in the cells of the $r \times c$ contingency table. Before presenting the hypotheses in the latter format, the reader should take note of the following with respect to [Tables 16.2](#) and [16.3](#). In both [Tables 16.2](#) and [16.3](#) four cells can be identified: a) Cell₁₁ is the upper left cell in each table (i.e., in Row 1 and Column 1 the cell with the observed frequency $O_{11} = 30$). In the case of Example 16.1, $O_{11} = 30$ represents the number of subjects exposed to **noise** who **helped the confederate**. In the case of Example 16.2, $O_{11} = 30$ represents the number of **introverts** who are **Democrats**; b) Cell₁₂ is the upper right cell in each table (i.e., in Row 1 and Column 2 the cell with the observed frequency $O_{12} = 70$). In the case of Example 16.1, $O_{12} = 70$ represents the number of subjects exposed to **noise** who **did not help the confederate**. In the case of Example 16.2, $O_{12} = 70$ represents the number of **introverts** who are **Republicans**; c) Cell₂₁ is the lower left cell in each table (i.e., in Row 2 and Column 1 the cell with the observed frequency $O_{21} = 60$). In the case of Example 16.1, $O_{21} = 60$ represents the number of subjects exposed to **no noise** who **helped the confederate**. In the case of Example 16.2, $O_{21} = 60$ represents the number of **extroverts** who are **Democrats**; d) Cell₂₂ is the lower right cell in each table (i.e., in Row 2 and Column 2 the cell with the observed frequency $O_{22} = 40$). In the case of Example 16.1, $O_{22} = 40$ represents the number of subjects exposed to **no noise** who **did not help the confederate**. In the case of Example 16.2, $O_{22} = 40$ represents the number of **extroverts** who are **Republicans**.

Alternative way of stating the null and alternative hypotheses for the chi-square test for homogeneity If the independent variable (which represents the different groups) is employed as the row variable, the null and alternative hypotheses can be stated as follows:

$$H_0: \text{In the underlying populations the samples represent, all of the proportions in the same column of the } r \times c \text{ table are equal}$$

H_1 : In the underlying populations the samples represent, all of the proportions in the same column of the $r \times c$ table are not equal for at least one of the columns

Viewing the above hypotheses in relation to the sample data in [Table 16.2](#), the null hypothesis states that there are an equal proportion of observations in Cell₁₁ and Cell₂₁. With respect to the sample data, the proportion of observations in Cell₁₁ is the proportion of subjects who are exposed to **noise** who **helped the confederate** (which equals $O_{11}/O_{1.} = 30/100 = .3$). The proportion of observations in Cell₂₁ is the proportion of subjects who are exposed to **no noise** who **helped the confederate** (which equals $O_{21}/O_{2.} = 60/100 = .6$). The null hypothesis also requires an equal proportion of observations in Cell₁₂ and Cell₂₂. The proportion of observations in Cell₁₂ is the proportion of subjects who are exposed to **noise** who **did not help the confederate** (which equals $O_{12}/O_{1.} = 70/100 = .7$). The proportion of observations in Cell₂₂ is the proportion of subjects who are exposed to **no noise** who **did not help the confederate** (which equals $O_{22}/O_{2.} = 40/100 = .4$).

Alternative way of stating the null and alternative hypotheses for the chi-square test of independence The null and alternative hypotheses for the **chi-square test of independence** can be stated as follows:

$$H_0: \pi_{ij} = (\pi_{i.})(\pi_{.j}) \text{ for all } r \times c \text{ cells.}$$

$$H_1: \pi_{ij} \neq (\pi_{i.})(\pi_{.j}) \text{ for at least one cell.}$$

Where: π represents the value of a proportion in the population

The above notation indicates that if the null hypothesis is true, in the underlying population represented by the sample for each of the $r \times c$ cells, the proportion of observations in a cell will equal the proportion of observations in the row in which the cell appears multiplied by the proportion of observations in the column in which the cell appears. This will now be illustrated with respect to Example 16.2. In illustrating the relationship described in the null hypothesis, the notation p is employed to represent the relevant proportions obtained for the sample data. If the null hypothesis is true, in the case of Cell₁₁ it is required that the proportion of observations in Cell₁₁ is equivalent to the product of the proportion of observations in Row 1 (which equals $p_{1.} = O_{1.}/n = 100/200 = .5$) and the proportion of observations in Column 1 (which equals $p_{.1} = O_{.1}/n = 90/200 = .45$). The result of multiplying the row and column proportions is $(p_{1.})(p_{.1}) = (.5)(.45) = .225$. Thus, if the null hypothesis is true, the proportion of observations in Cell₁₁ must equal $p_{11} = .225$.⁵ Consequently, if the value .225 is multiplied by 200, which is the total number of observations in [Table 16.3](#), the resulting value $(p_{11})(n) = (.225)(200) = 45$ is the number of observations that is expected in Cell₁₁ if the null hypothesis is true. The same procedure can be used for the remaining three cells to determine the number of observations that are required in each cell in order for the null hypothesis to be supported. In Section IV these values, which in actuality correspond to the expected frequencies of the cells, are computed for each of the four cells in [Table 16.3](#) (as well as [Table 16.2](#)).

IV. Test Computations

The computations for the **chi-square test for $r \times c$ tables** will be described for Example 16.1. The procedure to be described in this section when applied to Example 16.2 yields the identical result since: a) The computational procedure for the **chi-square test of independence** is identical to that employed for the **chi-square test for homogeneity**; and b) The identical data are

employed for Examples 16.1 and 16.2. [Table 16.4](#) summarizes the data and computations for Example 16.1.

Table 16.4 Chi-Square Summary Table for Example 16.1

Cell	O_{ij}	E_{ij}	$(O_{ij} - E_{ij})$	$(O_{ij} - E_{ij})^2$	$\frac{(O_{ij} - E_{ij})^2}{E_{ij}}$
Cell ₁₁ — Noise/Helped the confederate	30	45	-15	225	5.00
Cell ₁₂ — Noise/Did not help the confederate	70	55	15	225	4.09
Cell ₂₁ — No noise/Helped the confederate	60	45	15	225	5.00
Cell ₂₂ — No noise/Did not help the confederate	40	55	-15	225	4.09
$\Sigma O_{ij} = 200 \quad \Sigma E_{ij} = 200 \quad \Sigma(O_{ij} - E_{ij}) = 0$					$\chi^2 = 18.18$

The observed frequency of each cell (O_{ij}) is listed in Column 2 of [Table 16.4](#). Column 3 contains the expected cell frequencies (E_{ij}). In order to conduct the **chi-square test for $r \times c$ tables**, the observed frequency for each cell must be compared with its expected frequency. In order to determine the expected frequency of a cell, the data should be arranged in a contingency table that employs the format of [Table 16.2](#). The following protocol is then employed to determine the expected frequency of a cell: a) Multiply the sum of the observations in the row in which the cell appears by the sum of the observations in the column in which the cell appears; b) Divide n , the total number of observations, into the product that results from multiplying the row and column sums for the cell.

The computation of an expected cell frequency can be summarized by Equation 16.1.

$$E_{ij} = \frac{(O_{i.})(O_{.j})}{n} \quad \text{(Equation 16.1)}$$

Applying Equation 16.1 to Cell₁₁ in [Table 16.2](#) (i.e., **noise/helped the confederate**), the expected cell frequency can be computed as follows. The row sum is the total number of subjects who were exposed to **noise**. Thus, $O_{1.} = 100$. The column sum is the total number of subjects who **helped the confederate**. Thus, $O_{.1} = 90$. Employing Equation 16.1, the expected frequency for Cell₁₁ can now be computed: $E_{11} = [(O_{1.})(O_{.1})]/n = [(100)(90)]/200 = 45$. The expected frequencies for the remaining three cells in the 2×2 contingency table that summarizes the data for Example 16.1 are computed below:

$$\text{Cell}_{12} = [(O_{1.})(O_{.2})]/n = [(100)(110)]/200 = 55$$

$$\text{Cell}_{21} = [(O_{2.})(O_{.1})]/n = [(100)(90)]/200 = 45$$

$$\text{Cell}_{22} = [(O_{2.})(O_{.2})]/n = [(100)(110)]/200 = 55$$

Upon determining the expected cell frequencies, the test statistic for the **chi-square test for $r \times c$ tables** is computed with Equation 16.2.⁶

$$\chi^2 = \sum_{i=1}^r \sum_{j=1}^c \left[\frac{(O_{ij} - E_{ij})^2}{E_{ij}} \right] \quad \text{(Equation 16.2)}$$

The operations described by Equation 16.2 (which are the same as those described for computing the chi-square statistic for the **chi-square goodness-of-fit test**) are as follows: a) The expected frequency of each cell is subtracted from its observed frequency (summarized in Column 4 of [Table 16.4](#)); b) For each cell, the difference between the observed and expected frequency is squared (summarized in Column 5 of [Table 16.4](#)); c) For each cell, the squared difference between the observed and expected frequency is divided by the expected frequency of the cell (summarized in Column 6 of [Table 16.4](#)); and d) The value of chi-square is computed by summing all of the values in Column 6. For Example 16.1, Equation 16.2 yields the value $\chi^2 = 18.18$.⁷

Note that in [Table 16.4](#) the sums of the observed and expected frequencies are identical. This must always be the case, and any time these sums differ from one another, it indicates that a computational error has been made. It is also required that the sum of the differences between the observed and expected frequencies equals zero (i.e., $\sum(O_{ij} - E_{ij}) = 0$). Any time the latter value does not equal zero, it indicates an error has been made. Since all of the $(O_{ij} - E_{ij})$ values are squared in Column 5, the sum of Column 6, which represents the value of χ^2 , must always be a positive number. If a negative value for chi-square is obtained, it indicates that an error has been made. The only time χ^2 will equal zero is when $O_{ij} = E_{ij}$ for all $r \times c$ cells.

V. Interpretation of the Test Results

The obtained value $\chi^2 = 18.18$ is evaluated with [Table A4 \(Table of the Chi-Square Distribution\)](#) in the **Appendix**. A general discussion of the values in [Table A4](#) can be found in Section V of the **single-sample chi-square test for a population variance (Test 3)**. When the chi-square distribution is employed to evaluate the **chi-square test for $r \times c$ tables**, the degrees of freedom employed for the analysis are computed with Equation 16.3.

$$df = (r - 1)(c - 1) \quad \text{(Equation 16.3)}$$

The tabled critical values in [Table A4](#) for the **chi-square test for $r \times c$ tables** are always derived from the right tail of the distribution. The critical chi-square value for a specific value of alpha is the tabled value at the percentile that corresponds to the value $(1 - \alpha)$. Thus, the tabled critical .05 chi-square value (to be designated $\chi^2_{.05}$) is the tabled value at the 95th percentile. In the same respect, the tabled critical .01 chi-square value (to be designated $\chi^2_{.01}$) is the tabled value at the 99th percentile. In order to reject the null hypothesis, the obtained value of chi-square must be equal to or greater than the tabled critical value at the prespecified level of significance. The aforementioned guidelines for determining tabled critical chi-square values are employed when the alternative hypothesis is stated nondirectionally (which, as noted earlier, is generally the case for the **chi-square test for $r \times c$ tables**). The determination of tabled critical chi-square values in reference to a directional alternative hypothesis is discussed in Section VI.

The guidelines for a nondirectional analysis will now be applied to Example 16.1. Since $r = 2$ and $c = 2$, the degrees of freedom are computed to be $df = (2 - 1)(2 - 1) = 1$. The tabled critical .05 chi-square value for $df = 1$ is $\chi^2_{.05} = 3.84$, which as noted above is the tabled chi-square value at the 95th percentile. The tabled critical .01 chi-square value for $df = 1$ is $\chi^2_{.01} = 6.63$, which as noted above is the tabled chi-square value at the 99th percentile. Since the computed value $\chi^2 = 18.18$ is greater than both of the aforementioned critical values, the null hypothesis can be rejected at both the .05 and .01 levels. Rejection of the null hypothesis at the .01 level can be summarized as follows: $\chi^2(1) = 18.18, p < .01$.

The significant chi-square value obtained for Example 16.1 indicates that subjects who served in the **noise** condition **helped the confederate** significantly less than subjects who served

in the **no noise** condition. This can be confirmed by visual inspection of [Table 16.2](#), which reveals that twice as many subjects who served in the **no noise** condition **helped the confederate** than subjects who served in the **noise** condition.

As noted previously, the chi-square analysis described in this section also applies to Example 16.2, since the latter example employs the same data as Example 16.1. Thus, with respect to Example 16.2, the significant $\chi^2 = 18.18$ value allows the researcher to conclude that a subject's categorization on the **introvert–extrovert** dimension is associated with (i.e., not independent of) one's political affiliation. This can be confirmed by visual inspection of [Table 16.3](#), which reveals that **introverts** are more likely to be **Republicans** whereas **extroverts** are more likely to be **Democrats**.

It is important to note that Example 16.2 represents a correlational study, and as such does not allow a researcher to draw any conclusions with regard to cause and effect.⁸ To be more specific, the study does not allow one to conclude that a subject's categorization on the personality dimension **introvert–extrovert** is the cause of one's political affiliation (**Democrat** versus **Republican**), or vice versa (i.e., that political affiliation causes one to be an **introvert** versus an **extrovert**). Although it is possible that the two variables employed in a correlational study are causally related to one another, such studies do not allow one to draw conclusions regarding cause and effect, since they fail to control for the potential influence of confounding variables. Because of this, when studies which are evaluated with the **chi-square test of independence** (such as Example 16.2) yield a significant result, one can only conclude that in the underlying population the two variables have a correlation with one another that is some value other than zero (which is not commensurate with saying that one variable causes the other).

Studies such as that represented by Example 16.2 can also be conceptualized within the framework of a **natural experiment** (also referred to as an **ex post facto study**) which is discussed in the **Introduction** of the book. In the latter type of study, one of the two variables is designated as the independent variable, and the second variable as the dependent variable. The independent variable is (in contrast to the independent variable in a **true experiment**) a non-manipulated variable. A subject's score (or category in the case of Example 16.2) on a non-manipulated independent variable is based on some preexisting subject characteristic, rather than being a direct result of some manipulation on the part of the experimenter. Thus, if in Example 16.2 the **introvert–extrovert** dimension is designated as the independent variable, it represents a nonmanipulated variable, since the experimenter does not determine whether or not a subject becomes an **introvert** or an **extrovert**. Which of the two aforementioned categories a subject falls into is determined beforehand by “nature” (thus the term **natural experiment**). The same logic also applies if political affiliation is employed as the independent variable, since, like **introvert–extrovert**, the **Democrat–Republican** dichotomization is a preexisting subject characteristic.

In Example 16.1, however, the independent variable, which is whether or not a subject is exposed to **noise**, is a manipulated variable. This is the case, since the experimenter randomly determines those subjects who are assigned to the **noise** condition and those who are assigned to the **no noise** condition. As noted in the **Introduction**, an experiment in which the researcher manipulates the level of the independent variable to which a subject is assigned is referred to as a **true experiment**. In the latter type of experiment, by virtue of randomly assigning subjects to the different experimental conditions, the researcher is able to control for the effects of potentially confounding variables. Because of this, if a significant result is obtained in a **true experiment**, a researcher is justified in drawing conclusions with regard to cause and effect.

VI. Additional Analytical Procedures for the Chi-Square Test for $r \times c$ Tables and/or Related Tests

1. Yates' correction for continuity In Section I it is noted that, in actuality, the **chi-square test for $r \times c$ tables** employs a continuous distribution to approximate a discrete probability distribution. Under such conditions, some sources recommend that a correction for continuity be employed. As noted previously in the book, the correction for continuity is based on the premise that if a continuous distribution is employed to estimate a discrete distribution, such an approximation will inflate the Type I error rate. By employing the correction for continuity, the Type I error rate is ostensibly adjusted to be more compatible with the prespecified alpha level designated by the researcher. Sources that recommend the correction for continuity for the **chi-square test for $r \times c$ tables** only recommend that it be employed in the case of 2×2 contingency tables. Equation 16.4 (which was developed by Yates (1934)) is the continuity-corrected chi-square equation for 2×2 tables.

$$\chi^2 = \sum_{i=1}^r \sum_{j=1}^c \left[\frac{(|O_{ij} - E_{ij}| - .5)^2}{E_{ij}} \right] \quad (\text{Equation 16.4})$$

Note that by subtracting .5 from the absolute value of the difference between each set of observed and expected frequencies, the chi-square value derived with Equation 16.4 will be lower than the value computed with Equation 16.2.

Statisticians are not in agreement with respect to whether it is prudent to employ the correction for continuity described by Equation 16.4 with a 2×2 contingency table. To be more specific, various sources take the following positions with respect to what the most effective strategy is for evaluating 2×2 tables: a) Most sources agree that when the sample size for a 2×2 table is small (generally less than 20), the **Fisher exact test** (which is described later in this section) should be employed instead of the **chi-square test for $r \times c$ tables**. Cochran (1952, 1954) stated that in the case of 2×2 tables, the **chi-square test for $r \times c$ tables** should not be employed when $n < 20$, and that when $20 < n < 40$ the test should only be employed if all of the expected frequencies are at least equal to 5. Additionally, when $n > 40$ all expected frequencies should be equal to or greater than 1; b) Some sources recommend that for small sample sizes **Yates' correction for continuity** be employed. This recommendation assumes that the size of the sample is at least equal to 20 (since, when $n < 20$, the **Fisher exact test** should be employed), but less than some value that defines the maximum size of a small sample size with respect to the use of Yates' correction. Sources do not agree on what value of n defines the upper limit beyond which Yates' correction is not required; c) Some sources recommend that **Yates' correction for continuity** should always be employed with 2×2 tables, regardless of the sample size; d) To further confuse the issue, many sources take the position that **Yates' correction for continuity** should never be used, since the chi-square value computed with Equation 16.4 results in an overcorrection — i.e., it results in an overly conservative test; and e) Haber (1980, 1982) argues that alternative continuity correction procedures (including one developed by Haber) are superior to **Yates' correction for continuity**. Haber's (1980, 1982) continuity correction procedure is described in Zar (1999, pp. 494–495).

Table 16.5 illustrates the application of **Yates' correction for continuity** with Example 16.1. By employing Equation 16.4 the obtained value of chi-square is reduced to 16.98 (in contrast to the value $\chi^2 = 18.18$ obtained with Equation 16.2). Since the obtained value $\chi^2 = 16.98$ is greater than both $\chi^2_{.05} = 3.84$ and $\chi^2_{.01} = 6.83$, the null hypothesis can still be rejected at both the .05 and .01 levels. Thus, in this instance **Yates' correction for continuity** leads to the same conclusions as those reached when Equation 16.2 is employed.

Table 16.5 Chi-Square Summary Table for Example 16.1 Employing Yates' Correction for Continuity

Cell	O_{ij}	E_{ij}	$(O_{ij} - E_{ij} - .5)$	$(O_{ij} - E_{ij} - .5)^2$	$\frac{(O_{ij} - E_{ij} - .5)^2}{E_{ij}}$
Cell ₁₁ — Noise/ Helped the confederate	30	45	14.5	210.25	4.67
Cell ₁₂ — Noise/ Did not help the confederate	70	55	14.5	210.25	3.82
Cell ₂₁ — No noise/ Helped the confederate	60	45	14.5	210.25	4.67
Cell ₂₂ — No noise/ Did not help the confederate	40	55	14.5	210.25	3.82
	$\Sigma O_{ij} = 200$	$\Sigma E_{ij} = 200$			$\chi^2 = 16.98$

2. Quick computational equation for a 2×2 table Equation 16.5 is a quick computational equation that can be employed for the **chi-square test for $r \times c$ tables** in the case of a 2×2 table. Unlike Equation 16.2, it does not require that the expected cell frequencies be computed. The notation employed in Equation 16.5 is based on the model for a 2×2 contingency table summarized in Table 16.6.

Table 16.6 Model for 2×2 Contingency Table

	Column 1	Column 2	Row sums
Row 1	a	b	$a + b = n_1$
Row 2	c	d	$c + d = n_2$
Column sums	$a + c$	$b + d$	n

$$\chi^2 = \frac{n(ad - bc)^2}{(a + b)(c + d)(a + c)(b + d)} \quad (\text{Equation 16.5})$$

Where: a , b , c , and d represent the number of observations in the relevant cell

Using the model depicted in Table 16.6, by employing the appropriate observed cell frequencies for Examples 16.1 and 16.2, we know that $a = 30$, $b = 70$, $c = 60$, and $d = 40$. Substituting these values in Equation 16.5, the value $\chi^2 = 18.18$ is computed (which is the same chi-square value that is computed with Equation 16.2).

$$\chi^2 = \frac{200[(30)(40) - (70)(60)]^2}{(30 + 70)(60 + 40)(30 + 60)(70 + 40)} = 18.18$$

If **Yates' correction for continuity** is applied to a 2×2 table, Equation 16.6 is the continuity-corrected version of Equation 16.5.

$$\chi^2 = \frac{n(|ad - bc| - .5n)^2}{(a + b)(c + d)(a + c)(b + d)} \quad (\text{Equation 16.6})$$

Substituting the data for Examples 16.1 and 16.2 in Equation 16.6, the value $\chi^2 = 16.98$ is computed (which is the same continuity-corrected chi-square value computed with Equation 16.4).

$$\chi^2 = \frac{200[(30)(40) - (70)(60)]^2 - (.5)(200)}{(30 + 70)(60 + 40)(30 + 60)(70 + 40)} = 16.98$$

3. Evaluation of a directional alternative hypothesis in the case of a 2×2 contingency table
In the case of 2×2 contingency tables it is possible to employ a directional/one-tailed alternative hypothesis. Prior to reading this section, the reader may find it useful to review the relevant material on this subject in Section VII of the **chi-square goodness-of-fit test**.

In the case of a 2×2 contingency table, it is possible to make two directional predictions. In stating the null and alternative hypotheses, the following notation (in reference to the sample data) based on the model for a 2×2 contingency table described in [Table 16.6](#) will be employed.

$$p_1 = \frac{a}{a + b} = \frac{a}{n_1} \quad p_2 = \frac{c}{c + d} = \frac{c}{n_2}$$

The value p_1 represents the proportion of observations in Row 1 that falls in Cell a , while the value p_2 represents the proportion of observations in Row 2 that falls in Cell c . The analogous proportions in the underlying populations that correspond to p_1 and p_2 will be represented by the notation π_1 and π_2 . Thus, π_1 represents the proportion of observations in Row 1 in the underlying population that falls in Cell a , while the proportion π_2 represents the proportion of observations in Row 2 in the underlying population that falls in Cell c . Employing the aforementioned notation, it is possible to make either of the two following directional predictions for a 2×2 contingency table.

a) In the underlying population(s) the sample(s) represent, the proportion of observations in Row 1 that falls in Cell a is greater than the proportion of observations in Row 2 that falls in Cell c . The null hypothesis and directional alternative hypothesis for this prediction are stated as follows: $H_0: \pi_1 = \pi_2$ versus $H_1: \pi_1 > \pi_2$. With respect to Example 16.1, the latter alternative hypothesis predicts that a larger proportion of subjects in the **noise** condition will **help the confederate** than subjects in the **no noise** condition. In Example 16.2, the alternative hypothesis predicts that a larger proportion of **introverts** will be **Democrats** rather than **extroverts**.

b) In the underlying population(s) the sample(s) represent, the proportion of observations in Row 1 that falls in Cell a is less than the proportion of observations in Row 2 that falls in Cell c . The null hypothesis and directional alternative hypothesis for this prediction are stated as follows: $H_0: \pi_1 = \pi_2$ versus $H_1: \pi_1 < \pi_2$. With respect to Example 16.1, the latter alternative hypothesis predicts that a larger proportion of subjects in the **no noise** condition will **help the confederate** than subjects in the **noise** condition. In Example 16.2, the alternative hypothesis predicts that a larger proportion of **extroverts** will be **Democrats** rather than **introverts**.

As is the case for the **chi-square goodness-of-fit test**, if a researcher wants to evaluate a one-tailed alternative hypothesis at the .05 level, the appropriate critical value to employ is $\chi^2_{.90}$, which is the tabled chi-square value at the .10 level of significance. The latter value is represented by the tabled chi-square value at the 90th percentile (which demarcates the extreme 10% in the right tail of the chi-square distribution). If a researcher wants to evaluate a one-tailed/directional alternative hypothesis at the .01 level, the appropriate critical value to employ is $\chi^2_{.98}$, which is the tabled chi-square value at the .02 level of significance. The latter value is represented by the tabled chi-square value at the 98th percentile (which demarcates the extreme 2% in the right tail of the chi-square distribution).

If a one-tailed alternative hypothesis is evaluated for Examples 16.1 and 16.2, from [Table](#)

A4 it can be determined that for $df = 1$ the relevant tabled critical one-tailed .05 and .01 values are $\chi^2_{.90} = 2.71$ and $\chi^2_{.98} = 5.43$.⁹ Note that when one employs a one-tailed alternative hypothesis it is easier to reject the null hypothesis, since the one-tailed .05 and .01 critical values are less than the two-tailed .05 and .01 values (which for $df = 1$ are $\chi^2_{.05} = 3.84$ and $\chi^2_{.01} = 6.63$).¹⁰ In conducting a one-tailed analysis, it is important to note, however, if the obtained value of chi-square is equal to or greater than the tabled critical value at the prespecified level of significance, only one of the two possible alternative hypotheses can be supported. The alternative hypothesis that is supported is the one that is consistent with the data.

Since for Examples 16.1 and 16.2, the computed value $\chi^2 = 18.18$ is greater than both of the one-tailed critical values $\chi^2_{.90} = 2.71$ and $\chi^2_{.98} = 5.43$, the null hypothesis can be rejected at both the .05 and .01 levels, but only if the directional alternative hypothesis $H_1: \pi_1 < \pi_2$ is employed. If the directional hypothesis $H_1: \pi_1 > \pi_2$ is employed, the null hypothesis cannot be rejected, since the data are not consistent with the latter alternative hypothesis.

When evaluating contingency tables in which the number of rows and/or columns is greater than two, it is possible to run a **multi-tailed test**, (which as noted in the discussion of the **chi-square goodness-of-fit test** is the term that is sometimes used when there are more than two possible directional alternative hypotheses). It would be quite unusual to encounter the use of a multi-tailed analysis for an $r \times c$ table, which requires that a researcher determine all possible directional patterns/ordinal configurations for a set of data, and then predict one or more of the specific patterns that will occur. In the event one elects to conduct a multi-tailed analysis, the determination of the appropriate critical values is based on the same guidelines that are discussed for multi-tailed tests under the **chi-square goodness-of-fit test**.

4. Test 16c: The Fisher exact test In Section I it is noted that the chi-square distribution provides an approximation of the exact sampling distribution for a contingency table. In the case of 2×2 tables, the chi-square distribution is employed to approximate the hypergeometric distribution which will be discussed in this section. (The hypergeometric distribution is discussed in detail in Section IX (the **Addendum**) of the **binomial sign test for a single sample (Test 9)**.) As noted earlier, when $n < 20$ most sources recommend that the **Fisher exact test** (which employs exact hypergeometric probabilities) be employed to evaluate a 2×2 contingency table. **Table 16.6**, which is used earlier in this section to summarize a 2×2 table, will be employed to describe the model for the hypergeometric distribution upon which the **Fisher exact test** is based.

According to Daniel (1990) the **Fisher exact test**, which is also referred to as the **Fisher–Irwin test**, was simultaneously described by Fisher (1934, 1935), Irwin (1935), and Yates (1934). The test shares the same assumptions as those noted for the **chi-square test for $r \times c$ tables**, with the exception of the assumption regarding small expected frequencies (which reflects the limitations of the latter test with small sample sizes). Many sources note that an additional assumption of the **Fisher exact test** is that both the row and column sums of a 2×2 contingency table are predetermined by the researcher. In truth, this latter assumption is rarely met and, consequently, the test is used with 2×2 contingency tables involving small samples sizes when one or neither of the marginal sums is predetermined by the researcher. The **Fisher exact test** is more commonly employed with the model described for the **chi-square test of homogeneity** than it is with the model described for the **chi-square test of independence**.

Equation 16.7, which is the equation for a hypergeometrically distributed variable, allows for the computation of the exact probability (P) of obtaining a specific set of observed frequencies in a 2×2 contingency table. Equation 16.7, which uses the notation for the **Fisher exact test** model, is equivalent to Equation 9.15, which is more commonly employed to represent the general equation for a hypergeometrically distributed variable. Since Equation 16.7 involves the computation of combinations, the reader may find it useful to review the discussion of combinations in

Section IV of the **binomial sign test for a single sample**.

$$P = \frac{\binom{a+c}{a} \binom{b+d}{b}}{\binom{n}{a+b}} \quad (\text{Equation 16.7})$$

Equation 16.8 is a computationally more efficient form of Equation 16.7 which yields the same probability value.

$$P = \frac{(a+c)! (b+d)! (a+b)! (c+d)!}{n! a! b! c! d!} \quad (\text{Equation 16.8})$$

Example 16.3 (which is a small sample size version of Example 16.1) will be employed to illustrate the **Fisher exact test**.

Example 16.3 *A researcher conducts a study in order to evaluate the effect of noise on altruistic behavior. Each of the 12 subjects who participate in the experiment is randomly assigned to one of two experimental conditions. Subjects in both conditions are given a one-hour test which is ostensibly a measure of intelligence. During the test the six subjects in Group 1 are exposed to continual loud noise, which they are told is due to a malfunctioning generator. The six subjects in Group 2 are not exposed to any noise during the test. Upon completion of this stage of the experiment, each subject on leaving the room is confronted by a middle-aged man whose arm is in a sling. The man asks the subject if she would be willing to help him carry a heavy package to his car. In actuality, the man requesting help is an experimental confederate (i.e., working for the experimenter). The number of subjects in each group who help the man is recorded. One of the six subjects who were exposed to noise elects to help the man, while five of the six subjects who were not exposed to noise elect to help the man. Do the data indicate that altruistic behavior is influenced by noise?*

The data for Example 16.3, which can be summarized in the form of a 2×2 contingency table, are presented in [Table 16.7](#).

Table 16.7 Summary of Data for Example 16.3

	Helped the confederate	Did not help the confederate	Row sums
Noise	$a = 1$	$b = 5$	$a + b = n_1 = 6$
No noise	$c = 5$	$d = 1$	$c + d = n_2 = 6$
Column sums	$a + c = 6$	$b + d = 6$	$n = 12$

The null and alternative hypotheses for the **Fisher exact test** are most commonly stated using the format described in the discussion of the evaluation of a directional alternative hypothesis for a 2×2 contingency table. Thus, the null hypothesis and nondirectional alternative hypotheses are as follows:

$$H_0: \pi_1 = \pi_2$$

(In the underlying populations the samples represent, the proportion of observations in Row 1 (the **noise** condition) that falls in Cell a is equal to the proportion of observations in Row 2 (the **no**

noise condition) that falls in Cell *c*.)

$$H_1: \pi_1 \neq \pi_2$$

(In the underlying populations the samples represent, the proportion of observations in Row 1 (the **noise** condition) that falls in Cell *a* is not equal to the proportion of observations in Row 2 (the **no noise** condition) that falls in Cell *c*.)

The alternative hypothesis can also be stated directionally, as described in the discussion of the evaluation of a directional alternative hypothesis for a 2×2 contingency table — i.e., $H_1: \pi_1 > \pi_2$ or $H_1: \pi_1 < \pi_2$.¹¹

Employing Equations 16.7 and 16.8, the probability of obtaining the specific set of observed frequencies in Table 16.7 is computed to be $P = .039$.

Equation 16.7:

$$P = \frac{\binom{6}{1} \binom{6}{5}}{\binom{12}{6}} = \frac{\left[\frac{6!}{1! 5!} \right] \left[\frac{6!}{5! 1!} \right]}{\frac{12!}{6! 6!}} = .039$$

Equation 16.8:

$$P = \frac{6! 6! 6! 6!}{12! 1! 5! 5! 1!} = .039$$

In order to evaluate the null hypothesis, in addition to the probability $P = .039$ (which is the probability of obtaining the set of observed frequencies in Table 16.7) it is also necessary to compute the probabilities for any sets of observed frequencies that are even more extreme than the observed frequencies in Table 16.7. The only result that is more extreme than the result summarized in Table 16.7 is if all six subjects in the **no noise** condition **helped the confederate**, while all six subjects in the **noise** condition **did not help the confederate**. Table 16.8 summarizes the observed frequencies for the latter result.

Table 16.8 Most Extreme Possible Set of Observed Frequencies for Example 16.3

	Helped the confederate	Did not help the confederate	Row sums
Noise	$a = 0$	$b = 6$	$a + b = n_1 = 6$
No noise	$c = 6$	$d = 0$	$c + d = n_2 = 6$
Column sums	$a + c = 6$	$b + d = 6$	$n = 12$

Employing Equations 16.7 and 16.8, the probability of obtaining the set of observed frequencies in Table 16.8 is computed to be $P = .001$.

Equation 16.7:

$$P = \frac{\binom{6}{0} \binom{6}{6}}{\binom{12}{6}} = \frac{\left[\frac{6!}{0! 6!} \right] \left[\frac{6!}{6! 0!} \right]}{\frac{12!}{6! 6!}} = .001$$

Equation 16.8:

$$P = \frac{6! \ 6! \ 6! \ 6!}{12! \ 0! \ 6! \ 6! \ 0!} = .001$$

When $P = .001$ (the probability of obtaining the set of observed frequencies in Table 16.8) is added to $P = .039$, the resulting probability represents the likelihood of obtaining a set of observed frequencies that is equal to or more extreme than the set of observed frequencies in Table 16.7. The notation P_T will be used to represent the latter value. Thus, in our example, $P_T = .039 + .001 = .04$.¹²

The following guidelines are employed for Example 16.3 in evaluating the null hypothesis for the **Fisher exact test**.

a) If the nondirectional alternative hypothesis $H_1: \pi_1 \neq \pi_2$ is employed, the value of P_T (i.e., the probability of obtaining a set of observed frequencies equal to or more extreme than the set obtained in the study) must be equal to or less than $\alpha/2$. Thus, if the prespecified value of alpha is $\alpha = .05$, the obtained value of P_T must be equal to or less than $.05/2 = .025$. If the prespecified value of alpha is $\alpha = .01$, the obtained value of P_T must be equal to or less than $.01/2 = .005$.

b) If a directional alternative hypothesis is employed, the observed set of frequencies for the study must be consistent with the directional alternative hypothesis, and the value of P_T must be equal to or less than the prespecified value of alpha. Thus, if the prespecified value of alpha is $\alpha = .05$, the obtained value of P_T must be equal to or less than $.05$. If the prespecified value of alpha is $\alpha = .01$, the obtained value of P_T must be equal to or less than $.01$.

Employing the above guidelines, the following conclusions can be reached.

If $\alpha = .05$, the nondirectional alternative hypothesis $H_1: \pi_1 \neq \pi_2$ is not supported, since the obtained value $P_T = .04$ is greater than $.05/2 = .025$.

The directional alternative hypothesis $H_1: \pi_1 < \pi_2$ is supported, but only at the $.05$ level. This is the case, since the data are consistent with the latter alternative hypothesis, and the obtained value $P_T = .04$ is less than $\alpha = .05$. The latter alternative hypothesis is not supported at the $.01$ level, since $P_T = .04$ is greater than $\alpha = .01$.

The directional alternative hypothesis $H_1: \pi_1 > \pi_2$ is not supported, since it is not consistent with the data. In order for the data to be consistent with the alternative hypothesis $H_1: \pi_1 > \pi_2$, it is required that a larger proportion of subjects in the **noise** condition **helped the confederate** than subjects in the **no noise** condition.

To further clarify how to interpret a directional versus a nondirectional alternative hypothesis, consider Table 16.9 which presents all seven possible outcomes of observed cell frequencies for $n = 12$ in which the marginal sums (i.e., the row and column sums) equal six (which are the values for the marginal sums in Example 16.3).

The sum of the probabilities for the seven outcomes presented in Table 16.9 equals 1. This is the case, since the seven outcomes represent all the possible outcomes for the cell frequencies if the marginal sum of each of row and column equals six. As noted earlier, if a researcher evaluates the directional alternative hypothesis $H_1: \pi_1 < \pi_2$ for Example 16.3, he will only be interested in **Outcomes 1 and 2**. The combined probability for the latter two outcomes is $P_T = .04$, which is less than the one-tailed value $\alpha = .05$ (which represents the extreme 5% of the sampling distribution in one of the two tails of the distribution). Since the data are consistent with the directional alternative hypothesis $H_1: \pi_1 < \pi_2$ and $P_T = .04$ is less than $\alpha = .05$, the latter alternative hypothesis is supported.

If, however, the nondirectional alternative hypothesis $H_1: \pi_1 \neq \pi_2$ is employed, in addition to considering **Outcomes 1 and 2**, the researcher must also consider **Outcomes 6 and 7**, which

**Table 16.9 Possible Outcomes for Observed Cell Frequencies
If All Marginal Sums Equal 6, When $n = 12$**

Outcome 1: $P = .001$				Outcome 2: $P = .039$			
	Col. 1	Col. 2	Row sums		Col. 1	Col. 2	Row sums
Row 1	0	6	6	Row 1	1	5	6
Row 2	6	0	6	Row 2	5	1	6
Column sums	6	6	12	Column sums	6	6	12
Outcome 3: $P = .243$				Outcome 4: $P = .433$			
	Col. 1	Col. 2	Row sums		Col. 1	Col. 2	Row sums
Row 1	2	4	6	Row 1	3	3	6
Row 2	4	2	6	Row 2	3	3	6
Column sums	6	6	12	Column sums	6	6	12
Outcome 5: $P = .243$				Outcome 6: $P = .039$			
	Col. 1	Col. 2	Row sums		Col. 1	Col. 2	Row sums
Row 1	4	2	6	Row 1	5	1	6
Row 2	2	4	6	Row 2	1	5	6
Column sums	6	6	12	Column sums	6	6	12
Outcome 7: $P = .001$							
	Col. 1	Col. 2	Row sums				
Row 1	6	0	6				
Row 2	0	6	6				
Column sums	6	6	12				

are the analogous extreme outcomes in the opposite tail of the distribution. The latter set of outcomes also has a combined probability of .04. If the probability associated with **Outcomes 1 and 2** and **Outcomes 6 and 7** are summed, the resulting value $P_T = .04 + .04 = .08$ represents the likelihood in both tails of the distribution of obtaining an outcome equal to or more extreme than the outcome observed in Table 16.7. Since the value $P_T = .08$ is greater than the two-tailed value $\alpha = .05$, the nondirectional alternative hypothesis $H_1: \pi_1 \neq \pi_2$ is not supported. This is commensurate with saying that in order for the latter alternative hypothesis to be supported at the .05 level, in each of the tails of the distribution the maximum permissible probability value for outcomes that are equivalent to or more extreme than the observed outcome cannot be greater than the value $.05/2 = .025$. As noted earlier, since the computed probability in the relevant tail of the distribution equals .04 (which is greater than $.05/2 = .025$), the nondirectional alternative hypothesis is not supported.

If the directional alternative hypothesis $H_1: \pi_1 > \pi_2$ is employed the researcher is interested in **Outcomes 6 and 7**. As is the case for **Outcomes 1 and 2**, the combined probability for these two outcomes is $P_T = .04$, which is less than the one-tailed value $\alpha = .05$ (which represents the extreme 5% of the sampling distribution in the other tail of the distribution). However, since the data are not consistent with the directional alternative hypothesis $H_1: \pi_1 > \pi_2$, it is not supported.

To compare the results of the **Fisher exact test** with those that will be obtained if Example 16.3 is evaluated with the **chi-square test for $r \times c$ tables**, Equation 16.2 will be employed to evaluate the data in Table 16.7. Table 16.10 summarizes the chi-square analysis. Note that the expected frequency of each cell is 3, since when Equation 16.1 is employed, the value $E_{ij} = [(6)(6)]/12 = 3$ is computed for all $r \times c = 4$ cells.

Table 16.10 Chi-Square Summary Table for Example 16.3

Cell	O_{ij}	E_{ij}	$(O_{ij} - E_{ij})$	$(O_{ij} - E_{ij})^2$	$\frac{(O_{ij} - E_{ij})^2}{E_{ij}}$
Cell ₁₁ — Noise/Helped the confederate	1	3	-2	4	1.33
Cell ₁₂ — Noise/Did not help the confederate	5	3	2	4	1.33
Cell ₂₁ — No noise/Helped the confederate	5	3	2	4	1.33
Cell ₂₂ — No noise/Did not help the confederate	1	3	-2	4	1.33
	$\Sigma O_{ij} = 12$	$\Sigma E_{ij} = 12$	$\Sigma(O_{ij} - E_{ij}) = 0$		$\chi^2 = 5.32$

Since for $df = 1$, the obtained value $\chi^2 = 5.32$ is greater than the tabled critical two-tailed .05 value $\chi^2_{.05} = 3.84$, the nondirectional alternative hypothesis $H_1: \pi_1 \neq \pi_2$ is supported at the .05 level. It is not, however, supported at the .01 level, since $\chi^2 = 5.32$ is less than the tabled critical two-tailed .01 value $\chi^2_{.01} = 6.63$.

The directional alternative hypothesis $H_1: \pi_1 < \pi_2$ is supported at the .05 level, since the obtained value $\chi^2 = 5.32$ is greater than the tabled critical one-tailed .05 value $\chi^2_{.90} = 2.71$. The latter directional alternative hypothesis falls just short of being supported at the .01 level, since $\chi^2 = 5.32$ is less than the tabled critical one-tailed .01 value $\chi^2_{.98} = 5.43$.

Note that when the **Fisher exact test** is employed, the nondirectional alternative hypothesis $H_1: \pi_1 \neq \pi_2$ is not supported at the .05 level, yet it is supported at the .05 level when the **chi-square test for $r \times c$ tables** is used. Both the **Fisher exact test** and **chi-square test for $r \times c$ tables** allow the researcher to reject the null hypothesis at the .05 level if the directional alternative hypothesis $H_1: \pi_1 < \pi_2$ is employed. However, whereas the latter alternative hypothesis falls just short of significance at the .01 level when the **chi-square test for $r \times c$ tables** is used, it is further removed from being significant when the **Fisher exact test** is employed. The discrepancy between the two tests when they are applied to the same set of data involving a small sample size suggests that the chi-square approximation underestimates the actual probability associated with the observed frequencies and, consequently, increases the likelihood of committing a Type I error.

On the other hand, the result for the **chi-square test for $r \times c$ tables** for Example 16.3 will be totally consistent with the result obtained with the **Fisher exact test** if **Yates' correction for continuity** is employed in evaluating the data. If **Yates' correction** is employed, all of the $(O_{ij} - E_{ij})$ values in Table 16.10 become 1.5, which, when squared, equals 2.25. When the latter value is divided by the expected cell frequency of 3, it yields .75 which will be the entry for each cell in the last column of Table 16.10. The sum of the values in the latter column is $\chi^2 = 3$, which is the continuity-corrected chi-square value. Since $\chi^2 = 3$ is less than the tabled critical two-tailed values $\chi^2_{.05} = 3.84$ and $\chi^2_{.01} = 6.63$, the nondirectional alternative hypothesis is not supported. Since $\chi^2 = 3$ is greater than the tabled critical one-tailed .05 value $\chi^2_{.90} = 2.71$ but less than the tabled critical .01 one-tailed value $\chi^2_{.98} = 5.43$, the directional alternative hypothesis that is consistent with the data ($H_1: \pi_1 < \pi_2$) is supported, but only at the .05 level. This is the same conclusion that is reached when the **Fisher exact test** is employed.

5. Test 16d: The z test for two independent proportions The z test for two independent proportions is an alternative large sample procedure for evaluating a 2×2 contingency table. In point of fact, the z test for two independent proportions yields a result that is equivalent to

that obtained with the **chi-square test for $r \times c$ tables**. Later in this discussion it will be demonstrated that if both the **z test for two independent proportions** (which is based on the normal distribution) and the **chi-square test for $r \times c$ tables** are applied to the same set of data, the square of the z value obtained for the former test will equal the chi-square value obtained for the latter test.

The **z test for two independent proportions** is most commonly employed to evaluate the null and alternative hypotheses that are described for the **Fisher exact test** (which for a 2×2 contingency table are equivalent to the null and alternative hypotheses presented in Section III for the **chi-square test for homogeneity**). Thus, in reference to Example 16.1, employing the model for a 2×2 contingency table summarized by Table 16.6, the null hypothesis and non-directional alternative hypotheses for the **z test for two independent proportions** are as follows.

$$H_0: \pi_1 = \pi_2$$

(In the underlying populations the samples represent, the proportion of observations in Row 1 (the **noise** condition) that falls in Cell a is equal to the proportion of observations in Row 2 (the **no noise** condition) that falls in Cell c .)

$$H_1: \pi_1 \neq \pi_2$$

(In the underlying populations the samples represent, the proportion of observations in Row 1 (the **noise** condition) that falls in Cell a is not equal to the proportion of observations in Row 2 (the **no noise** condition) that falls in Cell c .)

An alternate but equivalent way of stating the above noted null hypothesis and nondirectional alternative hypothesis is as follows: $H_0: \pi_1 - \pi_2 = 0$ versus $H_1: \pi_1 - \pi_2 \neq 0$. As is the case with the **Fisher exact test** (as well as the **chi-square test for $r \times c$ tables**), the alternative hypothesis can also be stated directionally. Thus, the following two directional alternative hypotheses can be employed: $H_1: \pi_1 > \pi_2$ (which can also be stated as $H_1: \pi_1 - \pi_2 > 0$) or $H_1: \pi_1 < \pi_2$ (which can also be stated as $H_1: \pi_1 - \pi_2 < 0$).

Equation 16.9 is employed to compute the test statistic for the **z test for two independent proportions**.

$$z = \frac{p_1 - p_2}{\sqrt{p(1 - p)\left[\frac{1}{n_1} + \frac{1}{n_2}\right]}} \quad \text{(Equation 16.9)}$$

Where: n_1 represents the number of observations in Row 1
 n_2 represents the number of observations in Row 2
 $p_1 = a/(a + b) = a/n_1$ represents the proportion of observations in Row 1 that falls in Cell a . It is employed to estimate the population proportion π_1 .
 $p_2 = c/(c + d) = c/n_2$ represents the proportion of observations in Row 2 that falls in Cell c . It is employed to estimate the population proportion π_2 .
 $p = (a + c)/(n_1 + n_2) = (a + c)/n$. p is a pooled estimate of the proportion of observations in Column 1 in the underlying population.

The denominator of Equation 16.9, which represents a standard deviation of a sampling distribution of differences between proportions, is referred to as the **standard error of the difference between two proportions** (which is often summarized with the notation $s_{p_1 - p_2}$). This latter value is analogous to the **standard error of the difference** ($s_{\bar{X}_1 - \bar{X}_2}$), which is the

denominator of Equations 11.1, 11.2, 11.3, and 11.5 (which are all described in reference to the **t test for two independent samples (Test 11)**). Whereas the latter value is a standard deviation of a sampling distribution of difference scores between the means of two populations, the **standard error of the difference between two proportions** is a standard deviation of a sampling distribution of difference scores between proportions for two populations.

For Example 16.1 we either know or can compute the following values:¹³

$$a = 30 \quad c = 60 \quad n_1 = 100 \quad n_2 = 100$$

$$p_1 = \frac{a}{n_1} = \frac{30}{100} = .3 \quad p_2 = \frac{c}{n_2} = \frac{60}{100} = .6$$

$$p = \frac{a + c}{n_1 + n_2} = \frac{30 + 60}{100 + 100} = .45 \quad 1 - p = 1 - .45 = .55$$

Employing the above values in Equation 16.9, the value $z = -4.26$ is computed.

$$z = \frac{.3 - .6}{\sqrt{(.45)(.55)\left[\frac{1}{100} + \frac{1}{100}\right]}} = -4.26$$

The obtained value $z = -4.26$ is evaluated with **Table A1 (Table of the Normal Distribution)** in the **Appendix**. In **Table A1** the tabled critical two-tailed .05 and .01 values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed .05 and .01 values are $z_{.05} = 1.65$ and $z_{.01} = 2.33$. The following guidelines are employed in evaluating the null hypothesis:

a) If the nondirectional alternative hypothesis $H_1: \pi \neq \pi_2$ is employed, the null hypothesis can be rejected if the obtained absolute value of z is equal to or greater than the tabled critical two-tailed value at the prespecified level of significance.

b) If the directional alternative hypothesis $H_1: \pi_1 > \pi_2$ is employed, the null hypothesis can be rejected if $p_1 > p_2$, and the obtained value of z is a positive number that is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

c) If the directional alternative hypothesis $H_1: \pi_1 < \pi_2$ is employed, the null hypothesis can be rejected if $p_1 < p_2$, and the obtained value of z is a negative number with an absolute value that is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

Employing the above guidelines, the following conclusions can be reached.

Since the obtained absolute value $z = 4.26$ is greater than the tabled critical two-tailed values $z_{.05} = 1.96$ and $z_{.01} = 2.58$, the nondirectional alternative hypothesis $H_1: \pi \neq \pi_2$ is supported at both the .05 and .01 levels.

Since the obtained value of z is a negative number and absolute value $z = 4.26$ is greater than the tabled critical one-tailed values $z_{.05} = 1.65$ and $z_{.01} = 2.33$, the directional alternative hypothesis $H_1: \pi_1 < \pi_2$ is supported at both the .05 and .01 levels.

The directional alternative hypothesis $H_1: \pi_1 > \pi_2$ is not supported, since as previously noted, in order for it to be supported the following must be true: $p_1 > p_2$.

Note that the above conclusions for the analysis of Example 16.1 (as well as Example 16.2) with the **z test for two independent proportions** are consistent with the conclusions that are reached when the **chi-square test for $r \times c$ tables** is employed to evaluate the same set of data. In point of fact, the square of the z value obtained with Equation 16.9 will always be equal to the value of chi-square computed with Equation 16.2. This relationship can be confirmed by the

fact that in the example under discussion, $(z = -4.26)^2 = (\chi^2 = 18.18)$. It is also the case that the square of a tabled critical z value at a given level of significance will equal the tabled critical chi-square value at the corresponding level of significance. This is confirmed for the tabled critical two-tailed z and χ^2 values at the .05 and .01 levels of significance: $(z_{.05} = 1.96)^2 = (\chi^2_{.05} = 3.84)$ and $(z_{.01} = 2.58)^2 = (\chi^2_{.01} = 6.63)$.¹⁴

Yates' correction for continuity can also be applied to the z test for two independent proportions. Equation 16.10 is the continuity-corrected equation for the z test for two independent proportions.

$$z = \frac{[p_1 - p_2] \pm \left[\frac{1}{2} \right] \left[\frac{1}{n_1} + \frac{1}{n_2} \right]}{\sqrt{p(1 - p) \left[\frac{1}{n_1} + \frac{1}{n_2} \right]}} \quad (\text{Equation 16.10})$$

The following protocol is employed with respect to the numerator of Equation 16.10: a) If $(p_1 - p_2)$ is a positive number, the term $[1/2][(1/n_1) + (1/n_2)]$ is subtracted from $(p_1 - p_2)$; and b) If $(p_1 - p_2)$ is a negative number, the term $[1/2][(1/n_1) + (1/n_2)]$ is added to $(p_1 - p_2)$. An alternative way of computing the value of the numerator of Equation 16.10 is to subtract $[1/2][(1/n_1) + (1/n_2)]$ from the absolute value of $(p_1 - p_2)$, and then restore the original sign of the latter value.

Employing Equation 16.10, the continuity-corrected value $z = -4.12$ is computed.

$$z = \frac{[.3 - .6] + \left[\frac{1}{2} \right] \left[\frac{1}{100} + \frac{1}{100} \right]}{\sqrt{(.45)(.55) \left[\frac{1}{100} + \frac{1}{100} \right]}} = -4.12$$

Note that the absolute value of the continuity-corrected z value computed with Equation 16.10 will always be smaller than the absolute z value computed with Equation 16.9. As is the case when Equation 16.9 is employed, the square of the continuity-corrected z value will equal the continuity-corrected chi-square value computed with Equation 16.4. Thus, $(z = -4.12)^2 = (\chi^2 = 16.98)$.

By employing Equation 16.10, the obtained absolute value of z is reduced to 4.12 (when contrasted with the absolute value $z = 4.26$ computed with Equation 16.9). Since the absolute value $z = 4.12$ is greater than both $z_{.05} = 1.96$ and $z_{.01} = 2.58$, the nondirectional alternative hypothesis $H_1: \pi_1 \neq \pi_2$ is still supported at both the .05 and .01 levels. The directional alternative hypothesis $H_1: \pi_1 < \pi_2$ is also still supported at both the .05 and .01 levels, since the absolute value $z = 4.12$ is greater than both $z_{.05} = 1.65$ and $z_{.01} = 2.33$.

The protocol that has been described for the z test for two independent proportions assumes that the researcher employs the null hypothesis $H_0: \pi_1 = \pi_2$. If, in fact, the null hypothesis stipulates a difference other than zero between the two values π_1 and π_2 , Equation 16.11 is employed to compute the test statistic for the z test for two independent proportions.¹⁵

$$z = \frac{(p_1 - p_2) - (\pi_1 - \pi_2)}{\sqrt{\frac{p_1(1 - p_1)}{n_1} + \frac{p_2(1 - p_2)}{n_2}}} \quad (\text{Equation 16.11})$$

The use of Equation 16.11 is based on the assumption that $\pi_1 \neq \pi_2$. Whenever the latter is the case, instead of computing a pooled estimate for a common population proportion, it is appropriate to estimate a separate value for the proportion in each of the underlying populations (i.e., π_1 and π_2) by using the values p_1 and p_2 . This is in contrast to Equation 16.9, which computes a pooled p value (that represents the pooled estimate of the proportion of observations in Column 1 in the underlying populations). In the case of Equation 16.9, the computation of a pooled p value is based on the assumption that $\pi_1 = \pi_2$.

To illustrate the application of Equation 16.11, let us assume that the following null hypothesis and nondirectional alternative hypothesis are employed for Example 16.1: $H_0: \pi_1 - \pi_2 = -.1$ (which can also be written $H_0: \pi_2 - \pi_1 = .1$) versus $H_1: \pi_1 - \pi_2 \neq -.1$ (which can also be written $H_1: \pi_2 - \pi_1 \neq .1$). The null hypothesis states that in the underlying populations represented by the samples, the difference between the proportion of observations in Row 1 (the **noise** condition) that falls in Cell *a* and the proportion of observations in Row 2 (the **no noise** condition) that falls in Cell *c* is $-.1$. The alternative hypothesis states that in the underlying populations represented by the samples, the difference between the proportion of observations in Row 1 (the **noise** condition) that falls in Cell *a* and the proportion of observations in Row 2 (the **no noise** condition) that falls in Cell *c* is some value other than $-.1$.

In order for the nondirectional alternative hypothesis $H_1: \pi_1 - \pi_2 \neq -.1$ to be supported, the obtained absolute value of z must be equal to or greater than the tabled critical two-tailed value at the prespecified level of significance. The directional alternative hypothesis that is consistent with the data is $H_1: \pi_1 - \pi_2 < -.1$. In order for the latter alternative hypothesis to be supported, the sign of the obtained value of z must be negative, and the obtained absolute value of z must be equal to or greater than the tabled one-tailed critical value at the prespecified level of significance. The directional alternative hypothesis $H_1: \pi_1 - \pi_2 > -.1$ is not consistent with the data. Either a significant positive z value (in which case $p_1 - p_2 > 0$) or a significant negative z value (in which case $0 > (p_1 - p_2) > -.1$) is required to support the latter alternative hypothesis.

Employing Equation 16.11 for the above analysis, the value $z = -2.99$ is computed.

$$z = \frac{(.3 - .6) - (-.1)}{\sqrt{\frac{(.3)(.7)}{100} + \frac{(.6)(.4)}{100}}} = -2.99$$

Since the obtained absolute value $z = 2.99$ is greater than the tabled critical two-tailed .05 and .01 values $z_{.05} = 1.96$ and $z_{.01} = 2.58$, the nondirectional alternative hypothesis $H_1: \pi_1 - \pi_2 \neq -.1$ is supported at both the .05 and .01 levels. Thus, one can conclude that in the underlying populations the difference $(\pi_1 - \pi_2)$ is some value other than $-.1$. The directional alternative hypothesis $H_1: \pi_1 - \pi_2 < -.1$ is supported at both the .05 and .01 levels, since the obtained value $z = -2.99$ is a negative number and the absolute value $z = -2.99$ is greater than the tabled critical one-tailed values $z_{.05} = 1.65$ and $z_{.01} = 2.33$. Thus, if the latter alternative hypothesis is employed, one can conclude that in the underlying populations the difference $(\pi_1 - \pi_2)$ is some value that is less than $-.1$ (i.e., is a negative number with an absolute value larger than .1). As noted earlier, the directional alternative hypothesis $H_1: \pi_1 - \pi_2 > -.1$ is not supported, since it is not consistent with the data.

Yates' correction for continuity can also be applied to Equation 16.11 by employing the same correction factor in the numerator that is employed in Equation 16.10. Using the correction for continuity, the numerator of Equation 16.11 becomes:

$$(p_1 - p_2) - (\pi_1 - \pi_2) \pm \left[\frac{1}{2} \right] \left[\frac{1}{n_1} + \frac{1}{n_2} \right]$$

Without the correction for continuity, the value of the numerator of Equation 16.11 is $-.2$. Since $[1/2](1/100) + (1/100)] = .01$, using the guidelines outlined previously, the value of the numerator becomes $-.2 + .01 = -.19$. When the latter value is divided by the denominator (which for the example under discussion equals $.067$), it yields the continuity-corrected value $z = -2.84$. Thus, by employing the correction for continuity, the absolute value of z is reduced from $z = 2.99$ to $z = 2.84$. Since the absolute value $z = 2.84$ is greater than $z_{.05} = 1.96$ and $z_{.01} = 2.58$, the nondirectional alternative hypothesis $H_1: \pi_1 - \pi_2 \neq -.1$ is still supported at both the $.05$ and $.01$ levels. The directional alternative hypothesis $H_1: \pi_1 - \pi_2 < -.1$ is also still supported at both the $.05$ and $.01$ levels, since the absolute value $z = 2.84$ is greater than $z_{.05} = 1.65$ and $z_{.01} = 2.33$.

Cohen (1977, 1988) has developed a statistic called the ***h* index** that can be employed to compute the power of the ***z* test for two independent proportions**. The value h is an **effect size** index reflecting the difference between two population proportions. The concept of effect size is discussed in Section VI of the **single-sample *t* test (Test 2)**. It is discussed in greater detail in Section VI of the ***t* test for two independent samples**, and in Section IX (the **Addendum**) of the **Pearson product-moment correlation coefficient** under the discussion of **meta-analysis and related topics**.

The equation for the ***h* index** is $h = \phi_1 - \phi_2$ (where ϕ_1 and ϕ_2 are the arcsine transformed values for the proportions). Cohen (1977; 1988, Ch. 6) has derived tables that allow a researcher through use of the ***h* index** to determine the appropriate sample size to employ if one wants to test a hypothesis about the difference between two population proportions at a specified level of power. Cohen (1977; 1988, pp. 184–185) has proposed the following (admittedly arbitrary) h values as criteria for identifying the magnitude of an effect size: a) A **small effect size** is one that is greater than $.2$ but not more than $.5$; b) A **medium effect size** is one that is greater than $.5$ but not more than $.8$; and c) A **large effect size** is greater than $.8$.

6. Computation of confidence interval for a difference between proportions With large sample sizes, a confidence interval can be computed that identifies a range of values within which one can be confident to a specified degree that the true difference lies between the two population proportions π_1 and π_2 . Equation 16.12, which employs the normal distribution, is the general equation for computing the confidence interval for the difference between two population proportions. The notation employed in Equation 16.12 is identical to that used in the discussion of the ***z* test for two independent proportions**.

$$CI_{(1 - \alpha)} = (p_1 - p_2) \pm (z_{\alpha/2})(s_{p_1 - p_2}) \quad \text{(Equation 16.12)}$$

Where: $s_{p_1 - p_2} = \sqrt{[p_1(1 - p_1)]/n_1 + [p_2(1 - p_2)]/n_2}$
 $z_{\alpha/2}$ represents the tabled critical two-tailed value in the normal distribution, below which a proportion (percentage) equal to $[1 - (\alpha/2)]$ of the cases falls. If the proportion (percentage) of the distribution that falls within the confidence interval is subtracted from 1 (100%), it will equal the value of α .

Employing Equation 16.12, the 95% confidence interval for Examples 16.1/16.2 is computed below. In employing Equation 16.12, $(p_1 - p_2)$ (which is the numerator of Equation 16.9) represents the obtained difference between the sample proportions, $z_{.05}$ represents the tabled

critical two-tailed .05 value $z_{.05} = 1.96$, and $s_{p_1 - p_2}$ (which is the denominator of Equation 16.11) represents the **standard error of the difference between two proportions**.¹⁶

$$p_1 - p_2 = .3 - .6 = -.3$$

$$s_{p_1 - p_2} = \sqrt{\frac{(.3)(.7)}{100} + \frac{(.6)(.4)}{100}} = .067$$

$$CI_{.95} = (p_1 - p_2) \pm (z_{.05}) (s_{p_1 - p_2}) = -3 \pm (1.96)(.067) = -3 \pm .131$$

$$-.169 \geq (\pi_1 - \pi_2) \geq -.431$$

This result indicates that the researcher can be 95% confident (or the probability is .95) that the true difference between the population proportions falls within the range $-.431$ and $-.169$. Specifically, it indicates that the researcher can be 95% confident that the proportion for Population 1 (π_1) is less than the proportion for Population 2 (π_2) by a value that is greater than or equal to .169, but not greater than .431. The result can also be written as $.169 \leq (\pi_2 - \pi_1) \leq .431$, which indicates that the researcher can be 95% confident (or the probability is .95) that the proportion for Population 2 (π_2) is larger than the proportion for Population 1 (π_1) by a value that is greater than or equal to .169, but not greater than .431.

The 99% confidence interval, which results in a broader range of values, is computed below employing the tabled critical two-tailed .01 value $z_{.01} = 2.58$ in Equation 16.12 in lieu of $z_{.05} = 1.96$.

$$CI_{.99} = (p_1 - p_2) \pm (z_{.01}) (s_{p_1 - p_2}) = -3 \pm (2.58)(.067) = -3 \pm .173$$

$$-.127 \geq (\pi_1 - \pi_2) \geq -.473$$

Thus, the researcher can be 99% confident (or the probability is .99) that the proportion for Population 1 is less than the proportion for Population 2 by a value that is greater than or equal to .127, but not greater than .473.

7. Test 16c: The median test for independent samples The model for the **median test for independent samples** assumes that there are k independent groups, and that within each group each observation is categorized with respect to whether it is **above** or **below** a composite median value. In actuality, the **median test for independent samples** is a label that is commonly used when the **chi-square test for $r \times c$ tables**, the **z test for two independent proportions**, or the **Fisher exact test** is employed to evaluate the hypothesis that in each of k groups there is an equal proportion of observations that are **above** versus **below** a composite median. With large sample sizes, the **median test for independent samples** is computationally identical to the **chi-square test for $r \times c$ tables** (when $k \geq 2$) and the **z test for two independent proportions** (when $k = 2$). In the case of small sample sizes, the test is computationally identical to the **Fisher exact test** (when $k = 2$). [Table 16.6](#), which is used to summarize the model for the three aforementioned tests, can also be applied to the **median test for independent samples**. The two rows are employed to represent the two groups, and the two columns are used to represent the two categories on the dependent variable — specifically, whether a score falls **above** versus **below the median**. Example 16.4 will be employed to illustrate the **median test for two independent samples**.

Example 16.4 *A study is conducted to determine whether five-year old females are more likely than five-year old males to score above the population median on a standardized test of eye-hand coordination. One hundred randomly selected females and 100 randomly selected males are*

administered the test of eye-hand coordination, and categorized with respect to whether they score above or below the overall population median (i.e., the 50th percentile for both males and females). Table 16.11 summarizes the results of the study. Do the data indicate that there are gender differences in performance?

Table 16.11 Summary of Data for Example 16.4

	Above the median	Below the median	Row sums
Males	30	70	100
Females	60	40	100
Column sums	90	110	Total observations 200

Since Example 16.4 involves a large sample size, it can be evaluated with Equation 16.2, the equation for the **chi-square test for $r \times c$ tables** (as well as with Equation 16.9, the equation for the **z test for two independent proportions**). The reader should take note of the fact that the study described in Example 16.4 conforms to the model for the **chi-square test for homogeneity**. This is the case, since the row sums (i.e., the number of **males** and **females**) are predetermined by the researcher. Since it is consistent with the model for the latter test, the null and alternative hypotheses that are evaluated with the **median test for independent samples** are identical to those evaluated with the **chi-square test for homogeneity**, the **Fisher exact test**, and the **z test for two independent proportions**.¹⁷

Since the data for Example 16.4 are identical to the data for Examples 16.1/16.2, analysis of Example 16.4 with Equation 16.2 yields the value $\chi^2 = 18.18$ (which is the value obtained for Examples 16.1/16.2). Since (as noted earlier) $\chi^2 = 18.18$ is significant at both the .05 and .01 levels, one can conclude that **females** are more likely than **males** to score **above the median**.

In the case of the **median test for independent samples**, in the event that one or more subjects obtains a score that is equal to the population median, the following options are available for handling such scores: a) If the number of subjects who obtain a score that equals the median is reasonably large, a strong argument can be made for adding a third column to Table 16.11 for subjects who scored **at the median**. In such a case the contingency table is transformed into a 2×3 table; b) If a minimal number of subjects obtain a score at the median, such subjects can be dropped from the data; and c) Within each group, half the scores that fall at the median value are assigned to the **above the median** category and the other half to the **below the median** category. In the final analysis, the critical thing the researcher must be concerned with in employing any of the aforementioned strategies, is to make sure that the procedure he employs does not lead to misleading conclusions regarding the distribution of scores in the underlying populations.

The **median test for independent samples** can be extended to designs involving more than two groups. As an example, in Example 16.4 instead of evaluating the number of **males** and **females** who score **above** versus **below the median**, four groups of children representing different ethnic groups (e.g., **Caucasian**, **Asian-American**, **African-American**, **Native-American**) could be evaluated with respect to whether they score **above** versus **below the median**. In such a case, the data are summarized in the form of a 4×2 contingency table, with the four rows representing the four ethnic groups and the two columns representing **above** versus **below the median**.

It should be noted that some sources categorize the **median test for independent samples** as a test of ordinal data, since categorizing scores with respect to whether they are **above** versus **below the median** involves placing scores in one of two ordered categories. The reader should also be aware of the fact that it is possible to categorize scores on more than two ordered categories. As an example, **male** and **female** children can be categorized with respect to whether they

score in the **first quartile** (lower 25%), **second quartile** (25th to 50%), **third quartile** (50% to 75%), or **fourth quartile** (upper 25%) on the test of eye–hand coordination. In such a case, the data are summarized in the form of a 2×4 contingency table, with the two rows representing **males** and **females** and the four columns representing the four quartiles. It is also possible to have a design involving more than two groups of subjects (e.g., the four ethnic groups discussed above), and a dependent variable involving more than two ordered categories (e.g., four quartiles). The data for such a design are summarized in the form of a 4×4 contingency table. Finally, it is possible to have contingency tables in which both the row and the column variables are ordered. Although the **chi-square test for $r \times c$ tables** can be employed to evaluate a design in which both variables are ordered, alternative procedures may provide the researcher with more information about the relationship between the two variables. An example of such an alternative procedure is **Goodman and Kruskal’s gamma (Test 32)** discussed later in the book.

8. Extension of the chi-square test for $r \times c$ tables to contingency tables involving more than two rows and/or columns, and associated comparison procedures It is noted in the previous section that the **chi-square test for $r \times c$ tables** can be employed with tables involving more than two rows and/or columns. In this section larger contingency tables will be discussed, and within the framework of the discussion additional analytical procedures that can be employed with such tables will be described. Example 16.5 will be employed to illustrate the use of the **chi-square test for $r \times c$ tables** with a larger contingency table — specifically, a 4×3 table.

Example 16.5 *A researcher conducts a study in order to determine if there are differences in the frequency of biting among different species of laboratory animals. He selects random samples of four laboratory species from the stock of various animal supply companies. Sixty mice, 50 gerbils, 90 hamsters, and 80 guinea pigs are employed in the study. Each of the animals is handled over a two-week period, and categorized into one of the following three categories with respect to biting behavior: not a biter, mild biter, flagrant biter. Table 16.12 summarizes the data for the study. Do the data indicate that there are interspecies differences in biting behavior?*

Table 16.12 Summary of Data for Example 16.5

	Not a biter	Mild biter	Flagrant biter	Row sums
Mice	20	16	24	60
Gerbils	30	10	10	50
Hamsters	50	30	10	90
Guinea pigs	19	11	50	80
Column sums	119	67	94	Total observations 280

The study described in Example 16.5 conforms to the model for the **chi-square test for homogeneity**. This is the case, since the row sums (i.e., the number of animals representing each of the four species) is predetermined by the researcher. The row variable represents the independent variable in the study. The independent variable, which is comprised of four levels, is nonmanipulated, since it is based on a preexisting subject characteristic (i.e., species). The reader should take note of the fact that it is not necessary to have an equal number of subjects in each of the groups/categories that constitute the row variable. The column variable, which is comprised of three categories, is the biting behavior of the animals. The latter variable represents the dependent variable in the study. Note that the marginal sums for the column variable are not predetermined by the researcher.

As is the case with a 2×2 contingency table, Equation 16.1 is employed to compute the expected frequency for each cell. As an example, the expected frequency of Cell₁₁ (**mice/not a biter**) is computed as follows: $E_{11} = [(O_{1.})(O_{.1})]/n = [(60)(119)]/280 = 25.5$. In employing Equation 16.1, the value 60 represents the sum for Row 1 (which represents the total number of **mice**), the value 119 represents the sum for Column 1 (which represents the total number of animals categorized as **not a biter**), and 280 represents the total number of subjects/observations in the study.

After employing Equation 16.1 to compute the expected frequency for each of the $4 \times 3 = 12$ cells in the contingency table, Equation 16.2 is employed to compute the value $\chi^2 = 59.16$. The analysis is summarized in [Table 16.13](#).

Table 16.13 Chi-Square Summary Table for Example 16.5

Cell	O_{ij}	E_{ij}	$(O_{ij} - E_{ij})$	$(O_{ij} - E_{ij})^2$	$\frac{(O_{ij} - E_{ij})^2}{E_{ij}}$
Mice/Not a biter	20	25.50	-5.50	30.25	1.19
Mice/Mild biter	16	14.36	1.64	2.69	.19
Mice/Flagrant biter	24	20.14	3.86	14.90	.74
Gerbils/Not a biter	30	21.25	8.75	76.56	3.60
Gerbils/Mild biter	10	11.96	-1.96	3.84	.32
Gerbils/Flagrant biter	10	16.79	-6.79	46.10	2.75
Hamsters/Not a biter	50	38.25	11.75	138.06	3.61
Hamsters/Mild biter	30	21.54	8.46	71.57	3.32
Hamsters/Flagrant biter	10	30.21	-20.21	408.44	13.52
Guinea pigs/Not a biter	19	34.00	-15.00	225.00	6.62
Guinea pigs/Mild biter	11	19.14	-8.14	66.26	3.36
Guinea pigs/Flagrant biter	50	26.86	23.14	535.46	19.94
Column sums	280	280.00	0		$\chi^2 = 59.16$

Substituting the values $r = 4$ and $c = 3$ in Equation 16.3, the number of degrees of freedom for the analysis are $df = (4 - 1)(3 - 1) = 6$. Employing [Table A4](#), the tabled critical .05 and .01 chi-square values for $df = 6$ are $\chi^2_{.05} = 12.59$ and $\chi^2_{.01} = 16.81$. Since the computed value $\chi^2 = 59.16$ is greater than both of the aforementioned critical values, the null hypothesis can be rejected at both the .05 and .01 levels. By virtue of rejecting the null hypothesis, the researcher can conclude that the four species are not homogeneous with respect to biting behavior, or to be more precise, that at least two of the species are not homogeneous.

In the case of a 2×2 contingency table, a significant result indicates that the two groups employed in the study are not homogeneous with respect to the dependent variable. However, in the case of a larger contingency table, although a significant result indicates that at least two of the r groups are not homogeneous, the chi-square analysis does not indicate which of the groups differ from one another or which of the cells are responsible for the significant effect. Visual inspection of [Tables 16.12](#) and [16.13](#) suggests that the significant effect in Example 16.5 is most likely attributable to the disproportionately large number of **flagrant biters** among **guinea pigs**, and the disproportionately small number of **flagrant biters** among **hamsters**. In lieu of visual inspection (which is not a precise method for identifying the cells that are primarily responsible for a significant effect), the following two types of comparisons are among those that can be conducted.

Simple comparisons A **simple comparison** is a comparison between two of the r rows of an $r \times c$ contingency table (or two of the c columns). [Table 16.14](#) summarizes a simple comparison

that contrasts the biting behavior of **mice** with the biting behavior of **guinea pigs**. Note that in the simple comparison, the data for the other two species employed in the study (i.e., **gerbils** and **hamsters**) are not included in the analysis.

Table 16.14 Simple Comparison for Example 16.5

	Not a biter	Mild biter	Flagrant biter	Row sums
Mice	20	16	24	60
Guinea pigs	19	11	50	80
Column sums	39	27	74	Total observations 140

It should be noted that a simple comparison does not have to involve all of the columns of the contingency table. Thus, one can compare the two species **mice** and **guinea pigs**, but limit the comparison within those species to only those animals who are classified **not a biter** and **flagrant biter**. The resulting 2×2 contingency table for such a comparison will differ from Table 16.14 in that the second column (**mild biter**) is not included. As a result of omitting the latter column, the row sum for **mice** is reduced to 44 and the row sum for **guinea pigs** is reduced to 69. The total number of observations for the comparison is 113.

Complex comparisons A **complex comparison** is a comparison between two or more of the r rows of an $r \times c$ contingency table with one of the other rows or two or more of the other rows of the table.¹⁸ Table 16.5 summarizes an example of a complex comparison which contrasts the biting behavior of **guinea pigs** with the combined biting behavior of the other three species employed in the study (i.e., **mice**, **gerbils**, and **hamsters**).

As is the case for a simple comparison, a complex comparison does not have to include all of the columns on which the groups are categorized. Thus, one can compare the **mice**, **gerbils**, and **hamsters** with **guinea pigs**, but limit the comparison to only those animals who are classified **not a biter** and **flagrant biter**. The resulting 2×2 contingency table for such a comparison will differ from Table 16.15, in that the second column (**mild biter**) will not be included. As a result of omitting the latter column, the row sum for **mice**, **gerbils**, and **hamsters** is reduced to 144 and the row sum for **guinea pigs** is reduced to 69. The total number of observations for the comparison is 213.

Table 16.15 Complex Comparison for Example 16.5

	Not a biter	Mild biter	Flagrant biter	Row sums
Mice, Gerbils, and Hamsters	100	56	44	200
Guinea pigs	19	11	50	80
Column sums	119	67	94	Total observations 280

The null and alternative hypotheses for simple and complex comparisons are identical to those that are employed for evaluating the original $r \times c$ table, except for the fact that they are stated in reference to the specific cells involved in the comparison.

Sources are not in agreement with respect to what protocol is most appropriate to employ in conducting simple and/or complex comparisons following the computation of a chi-square value for an $r \times c$ contingency table. Among those sources that describe comparison procedures for $r \times c$ contingency tables are Keppel and Saufley (1980), Keppel *et al.* (1992), Marascuilo and

McSweeney (1977), and Siegel and Castellan (1988). Keppel *et al.* (1992) note that Wickens (1989) states that, as a general rule, the different protocols which have been developed for conducting comparisons yield comparable results. In discussing the general issue of partitioning contingency tables (i.e., breaking down the table for the purposes of conducting comparisons), most sources emphasize that whenever feasible, a researcher should plan a limited number of simple and/or complex comparisons prior to the data collection phase of a study, and that any comparisons one conducts should be meaningful at either a theoretical and/or practical level.¹⁹ In the discussion of comparisons in Section VI of the **chi-square goodness-of-fit test**, it is noted that when a limited number of comparisons are planned beforehand, most sources take the position that a researcher is not obliged to control the overall Type I error rate. However, when comparisons are not planned, there is general agreement that in order to avoid inflating the Type I error rate, the latter value should be adjusted. One way of adjusting the Type I error rate is to divide the maximum overall Type I error rate one is willing to tolerate by the total number of comparisons to be conducted. The resulting probability value can then be employed as the alpha level for each comparison that is conducted. To illustrate, if one intends to conduct three comparisons and does not want the overall Type I error rate for all of the comparisons to be greater than $\alpha = .05$, the alpha level to employ for each comparison is $\alpha/\text{number of comparisons} = .05/3 = .0167$. There are those who would argue the latter adjustment is too severe, since it substantially reduces the power associated with each comparison. In the final analysis, the researcher must be the one who decides what per comparison alpha level strikes an equitable balance in terms of the likelihood of committing a Type I error and the power associated with a comparison. Obviously, if a researcher employs a severely reduced alpha value, it may become all but impossible to detect actual differences that exist between the underlying populations. Before continuing this section, the reader may find it useful to review the discussion of comparisons for the **chi-square goodness-of-fit test**. A thorough overview of the issues involved in conducting comparisons can be found in Section VI of the **single-factor between-subjects analysis of variance (Test 21)**. In the remainder of this section, two comparison procedures for an $r \times c$ contingency table (based on Keppel *et al.* (1992) and Keppel and Saufley (1980)) will be described. The procedures to be described can be employed for both planned and unplanned comparisons.

Method 1 The first procedure to be described (which is derived from Keppel *et al.* (1992)) employs for both simple and complex comparisons the same protocol to evaluate a comparison contingency table as the protocol that is employed when the complete $r \times c$ table is evaluated. In the case of Example 16.5, Equation 16.2 is employed to evaluate the simple comparison summarized by the 2×3 contingency table in Table 16.14. The analysis assumes there is a total of 140 observations. Equation 16.1 is employed to compute the expected frequency of each cell — i.e., the sum of the observations in the row in which the cell appears is multiplied by the sum of the observations in the column in which the cell appears, with the resulting product divided by the total number of observations in the 2×3 contingency table. As an example, the expected frequency of Cell₁₁ (**mice/not a biter**) is computed as follows: $E_{11} = [(O_{1.})(O_{.1})]/n = [(60)(39)]/140 = 16.71$. In employing Equation 16.1, the value 60 represents the sum for Row 1 (which represents the total number of **mice**), the value 39 represents the sum for Column 1 (which represents the total number of **mice** and **guinea pigs** categorized as **not a biter**), and 140 represents the total number of observations in the table (i.e., **mice** and **guinea pigs**).

The sums for the two rows/species involved in the simple comparison under discussion are identical to the row sums for those species in the original 4×3 contingency table. The column sums, however, only represent the sums of the columns for the two species involved in the comparison, and are thus different from the column sums for all four species that are computed when

the original 4×3 contingency table is evaluated. [Table 16.16](#) summarizes the computation of the value $\chi^2 = 7.39$ (with Equation 16.2) for the simple comparison summarized in [Table 16.14](#).

Table 16.16 Chi-Square Summary Table for Simple Comparison in [Table 16.14](#) Employing Method 1

Cell	O_{ij}	E_{ij}	$(O_{ij} - E_{ij})$	$(O_{ij} - E_{ij})^2$	$\frac{(O_{ij} - E_{ij})^2}{E_{ij}}$
Mice/Not a biter	20	16.71	3.29	10.82	.65
Mice/Mild biter	16	11.57	4.43	19.62	1.70
Mice/Flagrant biter	24	31.71	-7.71	59.44	1.87
Guinea pigs/Not a biter	19	22.29	-3.29	10.82	.49
Guinea pigs/Mild biter	11	15.43	-4.43	19.62	1.27
Guinea pigs/Flagrant biter	50	42.29	7.71	59.44	1.41
Column sums	140	140.00	0		$\chi^2 = 7.39$

Substituting the values $r = 2$ and $c = 3$ in Equation 16.3, the number of degrees of freedom for the comparison are $df = (2 - 1)(3 - 1) = 2$. Employing [Table A4](#), the tabled critical .05 and .01 chi-square values for $df = 2$ are $\chi^2_{.05} = 5.99$ and $\chi^2_{.01} = 9.21$. Since the computed value $\chi^2 = 7.39$ is greater than $\chi^2_{.05} = 5.99$, the null hypothesis can be rejected at the .05 level. It cannot, however, be rejected at the .01 level, since $\chi^2 = 7.39$ is less than $\chi^2_{.01} = 9.21$. By virtue of rejecting the null hypothesis the researcher can conclude that **mice** and **guinea pigs**, the two species involved in the comparison, are not homogeneous with respect to biting behavior. Inspection of [Table 16.14](#) reveals that the significant difference can primarily be attributed to the fact that there are a disproportionately large number of **flagrant biters** among **guinea pigs**.

Method 2 An alternative and somewhat more cumbersome method for conducting both simple and complex comparisons described by Bresnahan and Shapiro (1966) and Castellan (1965) is presented in Keppel and Saufley (1980). Although most statisticians would consider the method to be described in this section as preferable to **Method 1**, in most cases the latter method will result in similar conclusions with regard to the hypothesis under study. The method to be described in this section is identical to **Method 1**, except for the fact that in computing the chi-square value, for each cell in the comparison contingency table the value $(O_{ij} - E_{ij})^2$ is divided by the expected frequency computed for the cell when the original $r \times c$ contingency table is evaluated (instead of the expected frequency for the cell based on the row and column sums in the comparison contingency table). Specifically, for each of the cells in the comparison contingency table, the following values are computed: a) The expected frequency for each cell is computed as it is for **Method 1** (i.e., using the row and column sums for the comparison contingency table and employing the number of observations in the comparison contingency table to represent the value of n); b) The values $(O_{ij} - E_{ij})$ and $(O_{ij} - E_{ij})^2$ are computed for each cell just as they are in **Method 1**; and c) In computing the values in the last column of the chi-square summary table, instead of dividing $(O_{ij} - E_{ij})^2$ by E_{ij} , it is divided by the expected frequency of the cell when all $r \times c$ cells in the original table are employed to compute the expected cell frequency. In the analysis to be described, the latter expected frequency for each cell is represented by the notation E'_{ij} . The steps noted above are illustrated in [Table 16.17](#), which summarizes the application of **Method 2** for computing the chi-square statistic for the simple comparison presented in [Table 16.14](#). Note that the value of E'_{ij} for each cell is the same as the value of the expected frequency for that cell in [Table 16.13](#).

**Table 16.17 Chi-Square Summary Table for Simple Comparison
in Table 16.14 Employing Method 2**

Cell	O_{ij}	E_{ij}	$(O_{ij} - E_{ij})$	$(O_{ij} - E_{ij})^2$	E'_{ij}	$\frac{(O_{ij} - E_{ij})^2}{E'_{ij}}$
Mice/Not a biter	20	16.71	3.29	10.82	25.50	.42
Mice/Mild biter	16	11.57	4.43	19.62	14.36	1.37
Mice/Flagrant biter	24	31.71	-7.71	59.44	20.14	2.95
Guinea pigs/Not a biter	19	22.29	-3.29	10.82	34.00	.32
Guinea pigs/Mild biter	11	15.43	-4.43	19.62	19.14	1.03
Guinea pigs/Flagrant biter	50	42.29	7.71	59.44	26.86	2.03
Column sums	140	140.00	0			$\chi^2 = 8.12$

As is the case when **Method 1** is employed, the null hypothesis can be rejected at the .05 level but not at the .01 level, since for $df = 2$, the computed value $\chi^2 = 8.12$ is greater than $\chi^2_{.05} = 5.99$, but less than $\chi^2_{.01} = 9.21$. Although the computed value $\chi^2 = 8.12$ is slightly larger than the value $\chi^2 = 7.39$ computed with **Method 1**, the difference between the two chi-square values is minimal. As noted previously, the two methods will generally yield approximately the same value.

Method 1 and **Method 2** will now be employed to evaluate the complex comparison summarized in Table 16.15. The results of these analyses are summarized in Tables 16.18 and 16.19.

**Table 16.18 Chi-Square Summary Table for Complex Comparison
in Table 16.15 Employing Method 1**

Cell	O_{ij}	E_{ij}	$(O_{ij} - E_{ij})$	$(O_{ij} - E_{ij})^2$	$\frac{(O_{ij} - E_{ij})^2}{E_{ij}}$
Mice, Gerbils, Hamsters/Not a biter	100	85.00	15.00	225.00	2.65
Mice, Gerbils, Hamsters/Mild biter	56	47.86	8.14	66.26	1.38
Mice, Gerbils, Hamsters/Flagrant biter	44	67.14	-23.14	535.46	7.98
Guinea pigs/Not a biter	19	34.00	-15.00	225.00	6.62
Guinea pigs/Mild biter	11	19.14	-8.14	66.26	3.46
Guinea pigs/Flagrant biter	50	26.86	23.14	535.46	19.34
Column sums	280	280.00	0		$\chi^2 = 42.03$

**Table 16.19 Chi-Square Summary Table for Complex Comparison
in Table 16.15 Employing Method 2**

Cell	O_{ij}	E_{ij}	$(O_{ij} - E_{ij})$	$(O_{ij} - E_{ij})^2$	E'_{ij}	$\frac{(O_{ij} - E_{ij})^2}{E'_{ij}}$
Mice, Gerbils, Hamsters/Not a biter	100	85.00	15.00	225.00	85.00	2.65
Mice, Gerbils, Hamsters/Mild biter	56	47.86	8.14	66.26	47.86	1.38
Mice, Gerbils, Hamsters/Flagrant biter	44	67.14	-23.14	535.46	67.14	7.98
Guinea pigs/Not a biter	19	34.00	-15.00	225.00	34.00	6.62
Guinea pigs/Mild biter	11	19.14	-8.14	66.26	19.14	3.46
Guinea pigs/Flagrant biter	50	26.86	23.14	535.46	26.86	19.94
Column sums	280	280.00	0			$\chi^2 = 42.03$

Although in the case of the complex comparison, **Method 1** and **Method 2** both yield the value $\chi^2 = 42.03$, the two methods will not always yield the same value. Substituting the values $r = 2$ and $c = 3$ in Equation 16.3, the number of degrees of freedom for the comparison are $df = (2 - 1)(3 - 1) = 2$. Employing **Table A4**, the tabled critical .05 and .01 chi-square values for $df = 2$ are $\chi^2_{.05} = 5.99$ and $\chi^2_{.01} = 9.21$. Since the computed value $\chi^2 = 42.03$ is greater than both of the aforementioned critical values, the null hypothesis can be rejected at both the .05 and .01 levels. By virtue of rejecting the null hypothesis, the researcher can conclude that a combined population of **mice, gerbils, and hamsters** is not homogeneous with a population of **guinea pigs** with respect to biting behavior. Inspection of **Table 16.15** reveals the latter can primarily be attributed to the discrepancy between the number of **guinea pigs** in the **flagrant biters** category and the number of **mice, gerbils, and hamsters** in the **not a biter** category.

As previously noted, if the two comparisons summarized in **Tables 16.14** and **16.15** are not planned prior to collecting the data, most sources would argue that each comparison should be evaluated at a lower alpha level. If one does not want the likelihood of committing at least one Type I error in the set of two comparisons to be greater than .05, one can adjust the alpha level as follows: Adjusted α level = α /number of comparisons = $.05/2 = .025$. Thus, in evaluating each of the comparisons, the tabled critical chi-square value at the .025 level is employed instead of the tabled critical .05 value $\chi^2_{.05} = 5.99$ (although as noted earlier some sources might consider the latter adjustment to be too severe). In **Table A4**, for the appropriate degrees of freedom, the tabled critical .025 value corresponds to the value listed under $\chi^2_{.975}$. In the case of $df = 2$, $\chi^2_{.975} = 7.38$. Note that for the simple comparison discussed in this section, the obtained chi-square value $\chi^2 = 7.39$ obtained with **Method 1** barely achieves significance if the latter critical value is used, whereas without the adjustment the latter result is significant at the .05 level by a comfortable margin. This example should serve to illustrate that by employing a lower alpha level, in addition to decreasing the likelihood of committing a Type I error, one also (by virtue of reducing the power of the test) decreases the likelihood of rejecting a false null hypothesis.

The rationale for presenting two comparison methods in this section is to demonstrate that although there is not a consensus among different sources with respect to what procedure should be employed for conducting comparisons, as a general rule, if a significant effect is present it will be identified regardless of which method one employs. Although **Method 1** is the simpler of the two methods described in this section, as noted earlier, most sources would probably take the position that **Method 1** is more subject to challenge on statistical grounds. Although in some instances there will be differences with respect to the precise probability values associated with the two methods (as well as the probabilities associated with other available methods), in most cases such differences will be trivial, and will thus be of little importance in terms of their practical and/or theoretical implications. In the final analysis, the per comparison alpha level one elects to employ (rather than the use of a different comparison procedure) is the most likely reason why two or more researchers may reach dramatically different conclusions with respect to a specific comparison. In such an instance, a replication study is the best available option for clarifying the status of the null hypothesis. Alternative procedures for conducting comparisons with contingency tables are described in Marascuilo and McSweeney (1977), Marascuilo and Serlin (1988), and Siegel and Castellan (1988).

9. The analysis of standardized residuals As noted in Section VI of the **chi-square goodness-of-fit test**, an alternative procedure for conducting comparisons (developed by Haberman (1973) and cited in Siegel and Castellan (1988)) involves the computation of **standardized residuals**. By computing standardized residuals, one is able to determine which cells are the major contributors to a significant chi-square value. The computation of residuals can be useful in reinforcing or clarifying information derived from the comparison procedures described in the

previous section, as well as providing additional information on the data contained in an $r \times c$ table. Through use of Equation 16.13, a standardized residual (R_{ij}) can be computed for each cell in an $r \times c$ contingency table.

$$R_{ij} = \frac{(O_{ij} - E_{ij})}{\sqrt{E_{ij}}} \quad (\text{Equation 16.13})$$

The value computed for a residual with Equation 16.13, which is interpreted as a normally distributed variable, is evaluated with [Table A1](#). Any residual with an absolute value that is equal to or greater than the tabled critical two-tailed .05 value $z_{.05} = 1.96$ is significant at the .05 level. Any residual that is equal to or greater than the tabled critical two-tailed .01 value $z_{.01} = 2.58$ is significant at the .01 level. Any cell in a contingency table which has a significant residual makes a significant contribution to the obtained chi-square value. For any cell that has a significant residual, one can conclude that the observed frequency of the cell differs significantly from its expected frequency. The sign of the standardized residual indicates whether the observed frequency of the cell is above (+) or below (–) the expected frequency. The sum of the squared residuals for all $r \times c$ cells will equal the obtained value of chi-square. The analysis of the residuals for Example 16.5 is summarized in [Table 16.20](#).

Table 16.20 Analysis of Residuals for Example 16.5

Cell	O_{ij}	E_{ij}	$(O_{ij} - E_{ij})$	$R_{ij} = \frac{(O_{ij} - E_{ij})}{\sqrt{E_{ij}}}$	$R_{ij} = \left[\frac{(O_{ij} - E_{ij})}{\sqrt{E_{ij}}} \right]^2$
Mice/Not a biter	20	25.50	–5.50	–1.09	1.19
Mice/Mild biter	16	14.36	1.64	.43	.19
Mice/Flagrant biter	24	20.14	3.86	.86	.74
Gerbils/Not a biter	30	21.25	8.75	1.90	3.61
Gerbils/Mild biter	10	11.96	–1.96	–.57	.33
Gerbils/Flagrant biter	10	16.79	–6.79	–1.66	2.76
Hamsters/Not a biter	50	38.25	11.75	1.90	3.61
Hamsters/Mild biter	30	21.54	8.46	1.82	3.32
Hamsters/Flagrant biter	10	30.21	–20.21	–3.68**	13.52
Guinea pigs/Not a biter	19	34.00	–15.00	–2.57*	6.62
Guinea pigs/Mild biter	11	19.14	–8.14	–1.86	3.46
Guinea pigs/Flagrant biter	50	26.86	23.14	4.46**	19.93
Column sums	280	280.00	0		$\sum R_{ij}^2 \chi^2 = 59.28$

*Significant at the .05 level.

**Significant at the .01 level.

Inspection of [Table 16.20](#) indicates that the residual computed for the following cells is significant: a) **guinea pigs/flagrant biters** — Since the absolute value $R_{ij} = 4.46$ computed for the residual is greater than $z_{.05} = 1.96$ and $z_{.01} = 2.58$, the residual is significant at both the .05 and .01 levels. The positive value of the residual indicates that the observed frequency of the cell is significantly above its expected frequency. The value of the residual for this cell is consistent with the fact that in the comparisons discussed in the previous section, the cell **guinea pigs/flagrant biters** appears to play a critical role in the significant effect that is detected; b) **hamsters/flagrant biter** — Since the absolute value $R_{ij} = 3.68$ computed for the residual is greater than $z_{.05} = 1.96$ and $z_{.01} = 2.58$, the residual is significant at both the .05 and .01 levels. The negative value of the residual indicates that the observed frequency of the cell is significantly

below its expected frequency. The value of the residual for this cell is consistent with the fact that in the comparisons discussed in the previous section the cell **hamsters/flagrant biter** appears to play a critical role in the significant effect that is detected; and c) **guinea pigs/not a biter** — since the absolute value $R_{ij} = 2.57$ computed for the residual is greater than $z_{.05} = 1.96$, but is less (albeit barely) than $z_{.01} = 2.58$, the residual is significant at the .05 level. The negative value of the residual indicates that the observed frequency of the cell is significantly below its expected frequency.

Four other cells in Table 16.20 approach being significant at the .05 level (**gerbils/not a biter**, **hamsters/not a biter**, **guinea pigs/mild biter**, **hamsters/mild biter**). The absolute value of the residual for all of the aforementioned cells is close to the tabled critical value $z_{.05} = 1.96$. Note that in Table 16.20, the sum of the squared residuals is essentially equal to the chi-square value computed in Table 16.13 for Example 16.5 (the minimal discrepancy is the result of rounding off error).

10. Sources for computing the power of the chi-square test for $r \times c$ tables Cohen (1977, 1988) has developed a statistic called the **w index** that can be employed to compute the power of the **chi-square test for $r \times c$ tables** (as well as the **chi-square goodness-of-fit test**). The value **w** is an **effect size** index reflecting the difference between expected and observed frequencies. The concept of effect size is discussed in Section VI of the **single-sample t test**. It is discussed in greater detail in Section VI of the **t test for two independent samples**, and in Section IX (the **Addendum**) of the **Pearson product-moment correlation coefficient** under the discussion of **meta-analysis and related topics**.

The equation for the **w index** is $w = \sqrt{\sum(P_{alt} - P_{null})^2 / P_{null}}$. The latter equation indicates the following: a) For each of the cells in the chi-square table, the proportion of cases hypothesized in the null hypothesis is subtracted from the proportion of cases hypothesized in the alternative hypothesis; b) The obtained difference in each cell is squared, and then divided by the proportion hypothesized in the null hypothesis for that cell; c) All of the values obtained for the cells in part b) are summed; and d) **w** represents the square root of the sum obtained in part c).

Cohen (1977, 1988, Ch. 7) has derived tables that allow a researcher to determine, through use of the **w index**, the appropriate sample size to employ if one wants to test a hypothesis about the difference between observed and expected frequencies in a chi-square table at a specified level of power. Cohen (1977, 1988, pp. 224–226) has proposed the following (admittedly arbitrary) **w** values as criteria for identifying the magnitude of an effect size: a) A **small effect size** is one that is greater than .1 but not more than .3; b) A **medium effect size** is one that is greater than .3 but not more than .5; and c) A **large effect size** is greater than .5.

11. Heterogeneity chi-square analysis for a 2×2 contingency table Let us suppose that a researcher conducts m independent studies (where $m \geq 2$), each of which evaluates the same hypothesis. In order to illustrate the analysis to be described in this section, we will assume that the null hypothesis evaluated in each study is that a particular type of kidney disease is equally likely to occur in males and females. The data for each study are summarized in a 2×2 contingency table, and each of the contingency tables is evaluated with the **chi-square test for homogeneity**. Although none of the m analyses yield a statistically significant result, visual inspection of the data suggests to the researcher that the disease occurs more frequently in females than males. The researcher suspects that because of the relatively small sample size employed in each study, the absence of significant results may be due to a lack of statistical power. In order to increase the power of the analysis, the researcher wants to combine the data for the m studies into one 2×2 contingency table, and evaluate the latter table with the **chi-square test for homogeneity**. This section will present a procedure (described in Zar (1999, pp. 500–504)) for

determining whether or not a researcher is justified in pooling data under such conditions. The procedure to be presented, which is referred to as **heterogeneity chi-square analysis**, was previously employed in reference to a one-dimensional chi-square table in Section VI of the **chi-square goodness-of-fit test**.

The null and alternative hypotheses that are evaluated with a **heterogeneity chi-square analysis** are as follows.

Null hypothesis H_0 : The m samples are derived from the same population (i.e., population homogeneity).

Alternative hypothesis H_1 : At least two of the m samples are not derived from the same population (i.e., population heterogeneity).

Table 16.21 summarizes the **heterogeneity chi-square analysis** conducted on $m = 3$ 2×2 contingency tables. Each table summarizes the results of a study evaluating the frequency of occurrence of the kidney disease in males and females. Part A of Table 16.21 presents the analysis of each study with the **chi-square test for homogeneity**. Column 2 for each of the studies contains the observed frequency for the relevant cell of the 2×2 contingency table. Thus, using the notation in Table 16.6, the following cells are represented in the contingency tables: **Cell a**: Males who develop the disease; **Cell b**: Males who do not develop the disease; **Cell c**: Females who develop the disease; **Cell d**: Females who do not develop the disease.

The following protocol is employed in the **heterogeneity chi-square analysis**: a) Employing the **chi-square test for homogeneity**, a chi-square value is computed for each of the individual studies. Zar (1999) notes that even though each table has one degree of freedom, the correction for continuity should not be employed in analyzing the individual contingency tables at this point in the analysis; b) The sum of the m chi-square values obtained in a) for the individual studies is computed. The latter value itself represents a chi-square value, and will be designated χ_{sum}^2 . In addition, the sum of the degrees of freedom for the m studies is computed. The latter degrees of freedom value, which will be designated df_{sum} , is obtained by summing the df values for each of the individual studies. Since in the case of a 2×2 contingency table $df = (r - 1)(c - 1) = 1$, the value of df_{sum} will equal the number of studies that are evaluated; c) The data for the m studies are combined into one table, and through use of the **chi-square test for homogeneity** a chi-square value, which will be designated χ_{pooled}^2 , is computed for the pooled data. The degrees of freedom for the table with the pooled data, which will be designated df_{pooled} , is equal to $df = 1$, since df for a 2×2 contingency table is $df = (r - 1)(c - 1) = 1$. Even though the table has one degree of freedom, the correction for continuity is not used in analyzing the table with the pooled data at this point in the analysis; d) The **heterogeneity chi-square analysis** is based on the premise that if the m samples are in fact homogeneous, the sum of the m individual chi-square values (χ_{sum}^2) should be approximately the same value as the chi-square value computed for the pooled data (χ_{pooled}^2). In order to determine the latter, the absolute value of the difference between the sum of the m chi-square values (obtained in b)) and the pooled chi-square value (obtained in c)) is computed. The obtained difference, which is itself a chi-square value, is the **heterogeneity chi-square value**, which will be designated χ_{het}^2 . Thus, $\chi_{het}^2 = |\chi_{sum}^2 - \chi_{pooled}^2|$. The null hypothesis will be rejected when there is a large difference between the values of χ_{sum}^2 and χ_{pooled}^2 . The value χ_{het}^2 , which represents the test statistic, is evaluated with a degrees of freedom value that is the sum of the degrees of freedom for the m individual studies (df_{sum}) less the degrees of freedom obtained for the table with the pooled data (df_{pooled}). Thus, $df_{het} = df_{sum} - df_{pooled}$. In order to reject the null hypothesis, the value χ_{het}^2 must be equal to or greater than the tabled critical value at the prespecified level of significance for df_{het} ; and e) If the null hypothesis is rejected the data cannot be pooled. If, however, the null

hypothesis is retained, the data can be pooled, and the computed value for χ^2_{pooled} is employed to evaluate the goodness-of-fit hypothesis. Zar (1999) notes, however, that the table for the pooled data should be reevaluated employing the correction for continuity, and the continuity-corrected χ^2_{pooled} value (which will be a little lower than the original χ^2_{pooled} value) should be employed to evaluate the relevant hypothesis for the contingency table.

The computed chi-square values for the three studies (summarized in **Part A** of [Table 16.21](#)) are $\chi^2_1 = 1.69$, $\chi^2_2 = 2.88$, and $\chi^2_3 = 2.63$. The total number of degrees of freedom employed for the three studies is $df_{sum} = (3)(1) = 3$ (i.e., the number of studies (3) multiplied by the number of degrees of freedom per study (1)). Since a single 2×2 contingency table is evaluated for the pooled data, the degrees of freedom for the latter table is $df_{pooled} = 1$. By summing the chi-square values for the three studies, we compute the value $\chi^2_{sum} = 1.69 + 2.88 + 2.63 = 7.20$. Since in **Part B** of [Table 16.21](#) we compute $\chi^2_{pooled} = 6.84$, the value for heterogeneity chi-square (computed in **Part C** of [Table 16.21](#)) is $\chi^2_{het} = |(\chi^2_{sum} = 7.20) - (\chi^2_{pooled} = 6.84)| = .36$. The degrees of freedom employed to evaluate the latter chi-square value are $df_{het} = (df_{sum} = 3) - (df_{pooled} = 1) = 2$. The tabled critical .05 and .01 chi-square values in [Table A4](#) for $df = 2$ are $\chi^2_{.05} = 5.99$ and $\chi^2_{.01} = 9.21$. Since the computed value $\chi^2_{het} = .36$ is less than $\chi^2_{.05} = 5.99$, the null hypothesis is retained. In other words we can conclude the three samples are homogeneous (i.e., come from the same population), and thus we can justify pooling the data into a single table.

As noted earlier, the correction for continuity is not employed in computing the value $\chi^2_{pooled} = 6.84$ for the pooled data in **Part B** of [Table 16.21](#). The data for the pooled contingency table are now reevaluated with the **chi-square test for homogeneity**, employing the correction for continuity. The continuity-corrected chi-square value (obtained in **Part D** of [Table 16.21](#)) is $\chi^2_{pooled} = 6.02$. The degrees of freedom for the pooled contingency table are $df = (r - 1)(c - 1) = 1$. The tabled critical .05 and .01 values in [Table A4](#) for $df = 1$ are $\chi^2_{.05} = 3.84$ and $\chi^2_{.01} = 6.63$. Since the value $\chi^2_{pooled} = 6.02$ is larger than $\chi^2_{.05} = 3.84$, the null hypothesis for the data in the contingency table can be rejected at the .05 level (but not at the .01 level). In other words, with respect to the pooled data, we can conclude that in the case of at least one of the cells, there is a difference between its observed and expected frequency. Inspection of the data suggests that the disease occurs more frequently in females than it does in males. A more detailed discussion of the **heterogeneity chi-square analysis** can be found in Zar (1999).

It should be emphasized that a researcher should employ common sense in applying the heterogeneity chi-square analysis described in this section. To be more specific, there may be occasions when even though the computed value of χ^2_{het} is not significant, in spite of the latter it would not be recommended that the researcher pool the data from two or more smaller tables. To be more specific, one should not pool data from two or more tables employing small sample sizes (which, when evaluated individually, fail to yield a significant chi-square value) in order to obtain a significant pooled chi-square value, when there is an obvious inconsistency in the cell proportions for two or more of the tables. In other words, when the data from m tables are pooled, the proportion of cases in the cells of each of the m tables should be approximately the same. Everitt (1977, 1992) and Fleiss (1981) recommend alternative procedures for pooling the data from multiple chi-square tables.

Another procedure that can be employed to combine the information in a set of 2×2 contingency tables is the **Mantel-Haenszel method** (Mantel and Haenszel (1959)). Pagano and Gauvreau (1993), who provide a detailed description of the procedure, note that the **Mantel-Haenszel method** allows a researcher do the following with a set of m 2×2 contingency tables: a) Evaluate whether the tables are homogeneous; b) Compute a summary **odds ratio** (which is discussed in the next section) for the tables; c) Compute a confidence interval for the **odds ratio**;

Table 16.21 Heterogeneity Chi-Square Analysis for Three 2×2 Contingency Tables

A. Chi-square analysis of three individual studies					
Cell	O_{ij}	E_{ij}	$(O_{ij} - E_{ij})$	$(O_{ij} - E_{ij})^2$	$\frac{(O_{ij} - E_{ij})^2}{E_{ij}}$
Study 1					
(a) Male/Disease	12	14.5	-2.5	6.25	.43
(b) Male/No disease	17	14.5	2.5	6.25	.43
(c) Female/Disease	18	15.5	2.5	6.25	.40
(d) Female/No disease	13	15.5	-2.5	6.25	.40
$\Sigma O_{ij} = 60$		$\Sigma E_{ij} = 60$	$\Sigma (O_{ij} - E_{ij}) = 0$		$\chi_1^2 = 1.69$
Study 2					
(a) Male/Disease	10	13	-3	9	.69
(b) Male/No disease	16	13	3	9	.69
(c) Female/Disease	15	12	3	9	.75
(d) Female/No disease	9	12	-3	9	.75
$\Sigma O_{ij} = 50$		$\Sigma E_{ij} = 50$	$\Sigma (O_{ij} - E_{ij}) = 0$		$\chi_2^2 = 2.88$
Study 3					
(a) Male/Disease	6	8.55	-2.55	6.50	.76
(b) Male/No disease	12	9.45	2.55	6.50	.69
(c) Female/Disease	13	10.45	2.55	6.50	.62
(d) Female/No disease	9	11.55	-2.55	6.50	.56
$\Sigma O_{ij} = 40$		$\Sigma E_{ij} = 40$	$\Sigma (O_{ij} - E_{ij}) = 0$		$\chi_3^2 = 2.63$
Sum of chi-square values for three studies =			$\chi_{sum}^2 = 1.69 + 2.88 + 2.63 = 7.20$		
B. Chi-square analysis of pooled data					
Pooled data for $m = 3$ studies					
Cell	O_{ij}	E_{ij}	$(O_{ij} - E_{ij})$	$(O_{ij} - E_{ij})^2$	$\frac{(O_{ij} - E_{ij})^2}{E_{ij}}$
(a) Male/Disease	28	36.01	-8.01	64.16	1.78
(b) Male/No disease	45	36.99	8.01	64.16	1.73
(c) Female/Disease	46	37.99	8.01	64.16	1.69
(d) Female/No disease	31	39.01	-8.01	64.16	1.64
$\Sigma O_{ij} = 150$		$\Sigma E_{ij} = 60$	$\Sigma (O_{ij} - E_{ij}) = 0$		$\chi_{pooled}^2 = 6.84$
C. Heterogeneity of chi-square analysis					
Heterogeneity chi-square = Sum of chi-square values for four studies – Pooled chi-square value					
$\chi_{het}^2 = (\chi_{sum}^2 = 7.20) - (\chi_{pooled}^2 = 6.84) = .36$					
D. Continuity-corrected chi-square analysis of pooled data					
Pooled data for $m = 3$ studies (continuity-corrected)					
Cell	O_{ij}	E_{ij}	$ O_{ij} - E_{ij} - .5$	$(O_{ij} - E_{ij} - .5)^2$	$\frac{(O_{ij} - E_{ij} - .5)^2}{E_{ij}}$
(a) Male/Disease	28	36.01	7.51	56.40	1.57
(b) Male/No disease	45	36.99	7.51	56.40	1.52
(c) Female/Disease	46	37.99	7.51	56.40	1.48
(d) Female/No disease	31	39.01	7.51	56.40	1.45
$\Sigma O_{ij} = 150$		$\Sigma E_{ij} = 60$	$\Sigma (O_{ij} - E_{ij}) = 0$		$\chi_{pooled}^2 = 6.02$

and d) Test the general hypothesis that each table was designed to evaluate (Pagano and Gauvreau (1993, p. 354)). Other sources that discuss the **Mantel-Haenszel method** are Conover (1999), Hollander and Wolfe (1999), Rosner (1995), and Sprent (1993). **Meta-analysis** (which is discussed in Section IX (the **Addendum**) of the **Pearson product-moment correlation coefficient**) can be also employed to obtain a combined result for multiple 2×2 contingency tables that evaluate the same general hypothesis (although meta-analysis does not pool all of the data into a single 2×2 table).

12. Measures of association for $r \times c$ contingency tables Prior to reading this section the reader may find it useful to review the discussion of **magnitude of treatment effect** (which is a measure of the degree of association between two or more variables) in Section VI of the ***t* test for two independent samples**. The computed chi-square value for an $r \times c$ contingency table does not provide a researcher with precise information regarding the size of the **treatment effect** present in the data. The reason why a chi-square value computed for a contingency table is not an accurate index of the degree of association between the two variables is because the chi-square value is a function of both the total sample size and the proportion of observations in each of the $r \times c$ cells of the table. The degree of association, on the other hand, is independent of the total sample size, and is only a function of the cell proportions. In point of fact, the magnitude of the computed chi-square statistic is directly proportional to the total sample size employed in a study.

To illustrate the latter point, consider Table 16.22 which presents a different set of data for Example 16.1. In actuality, the effect size for the data presented in Table 16.22 is the same as the effect size in Table 16.2, and the only difference between the two tables is that in Table 16.22 the total sample size and the number of observations in each of the cells are one-half of the corresponding values listed in Table 16.2. If Equation 16.2 is applied to the data presented in Table 16.22, the value $\chi^2 = 9.1$ is computed. Note that the latter value is one-half of $\chi^2 = 18.18$, which is the value computed for Table 16.2. Thus, even though the same proportion of observations appears in the corresponding cells of the two tables, the chi-square value computed for each table is directly proportional to the total sample size.

Table 16.22 Summary of Data for Example 16.1 With Reduced Sample Size				
	Helped the confederate	Did not help the confederate	Row sums	
Noise	15	35	50	
No noise	30	20	50	
Column sums	45	55	Total observations	100

A number of different measures of association/correlation that are independent of sample size can be employed as indices of the magnitude of a treatment effect for an $r \times c$ contingency table. In this section the following measures of association will be described: a) **Test 16f: The contingency coefficient**; b) **Test 16g: The phi coefficient**; c) **Test 16h: Cramér's phi coefficient**; d) **Test 16i: Yule's *Q***; and e) **Test 16j: The odds ratio**.

As a general rule (although there are some exceptions), the value computed for a measure of association/correlation will usually fall within a range of values between 0 and +1 or between -1 and +1. Whereas a value of 0 indicates no relationship between the two variables, an absolute value of 1 indicates a maximum relationship between the variables. Consequently, the closer the absolute value of a measure of association is to 1, the stronger the relationship between the variables. As noted above, some measures of association can assume values in the range between -1 and +1. In such cases, the absolute value of the measure indicates the strength of the

relationship, and the sign of the measure indicates the direction of the relationship — i.e., the pattern of observations among the cells of a contingency table. Before continuing this section the reader may find it useful to read Section I of the **Pearson product-moment correlation coefficient**, which provides a general discussion of correlation/association.

Measures of association for $r \times c$ contingency tables can be evaluated with respect to statistical significance. In the case of a number of the measures of association to be discussed in this section, if the computed chi-square value for the contingency table is statistically significant at a given level of significance, the measure of association computed for the contingency table will be significant at the same level of significance. In most instances, the null hypothesis and nondirectional alternative hypothesis evaluated with reference to a measure of association are as follows:²⁰

Null hypothesis The correlation/degree of association between the two variables in the underlying population is zero.

Alternative hypothesis The correlation/degree of association between the two variables in the underlying population is some value other than zero.

The same guidelines discussed earlier in reference to employing a directional alternative hypothesis for the **chi-square test for $r \times c$ tables** can also be applied if one wants to state the alternative hypothesis for a measure of association directionally.

Since the different measures of association that can be computed for a contingency table do not employ the same criteria in measuring the strength of the relationship between the two variables, if two or more measures are applied to the same set of data they may not yield comparable coefficients of association. Although in the material to follow, there will be some discussion of factors that can be taken into account in considering which of the various measures of association to employ, in most cases one measure is not necessarily superior to another in terms of providing information about a contingency table. Indeed, Conover (1980, 1999) notes that the choice of which measure to employ is based more on prevailing tradition than it is on statistical considerations.

Test 16f: The contingency coefficient (C) The **contingency coefficient** (also known as **Pearson's contingency coefficient**) is a measure of association that can be computed for an $r \times c$ contingency table of any size. The value of the **contingency coefficient**, which will be represented with the notation C , is computed with Equation 16.14.

$$C = \sqrt{\frac{\chi^2}{\chi^2 + n}} \quad \text{(Equation 16.14)}$$

Where: χ^2 is the computed chi-square value for the contingency table
 n is the total number of observations in the contingency table

Since n can never equal zero, the value of C can never equal 1. Consequently, the range of values C may assume is $0 \leq C < +1$. One limitation of the contingency coefficient is that its upper limit (i.e., the highest value it can attain) is a function of the number of rows and columns in the $r \times c$ contingency table. The upper limit of C (represented by C_{\max}) can be determined with Equation 16.15.

$$C_{\max} = \sqrt{\frac{k-1}{k}} \quad (\text{Equation 16.15})$$

Where: k represents the smaller of the two values of r and c in the contingency table

Employing Equation 16.15 for a 2×2 contingency table, we can determine that the maximum value for such a table is $C_{\max} = \sqrt{(2-1)/2} = .71$.

Employing Equation 16.14, the value $C = .29$ is computed as the value of the **contingency coefficient** for Examples 16.1/16.2.

$$C = \sqrt{\frac{18.18}{18.18 + 200}} = .29$$

Note that the value $C = .29$ is also obtained for Table 16.21 (which as noted earlier has the same effect size but half the sample size as Tables 16.2/16.3): $C = \sqrt{(9.1)/(9.1 + 100)} = .29$.

As noted in the introductory remarks on measures of association, the computed value $C = .29$ will be statistically significant at both the .05 and .01 levels, since the computed value $\chi^2 = 18.18$ for Tables 16.2/16.3 (as well as the computed value $\chi^2 = 9.1$ for Table 16.21) is significant at the aforementioned levels of significance. Thus, one can conclude that in the underlying population the **contingency coefficient** between the two variables is some value other than zero.

The reader should take note of the fact that if the value of n is reduced, but the effect size present in Tables 16.1/16.2/16.21 is maintained, at some point the chi-square value will not achieve significance. Although in such a case Equation 16.14 will yield the value $C = .29$, the latter value will not be statistically significant. This is the case, since in order for the value of C to be significant, the computed value of chi-square must be significant.

Ott *et al.* (1992) note that among the disadvantages associated with the **contingency coefficient** is that it will always be less than 1, even when the two variables are totally dependent on one another. In addition, **contingency coefficients** that have been computed for two or more tables can only be compared with one another if all of the tables have the same number of rows and columns. One suggestion that is made to counteract the latter problems is to employ Equation 16.16 to compute an adjusted value for the **contingency coefficient**.

$$C_{\text{adj}} = \frac{C}{C_{\max}} \quad (\text{Equation 16.16})$$

By employing Equation 16.16, if a perfect association between the variables exists, the value of C_{adj} will equal 1. If Equation 16.16 is employed for Examples 16.1/16.2 and Table 16.21, the value $C_{\text{adj}} = .29/.71 = .41$ is computed. It should be pointed out that although the use of C_{adj} allows for better comparison between tables of unequal size, it still does not allow one to compare such tables with complete accuracy.

In the section that discusses the computation of the power of the **chi-square test for $r \times c$ tables**, it notes that Cohen (1977, 1988) has developed a measure of effect size for the **chi-square test for $r \times c$ tables** called the **w index**. It also notes that Cohen (1977, 1988; pp. 224–226) has proposed the following (admittedly arbitrary) w values as criteria for identifying the magnitude of an effect size: a) A **small effect size** is one that is greater than .1 but not more than .3; b) A **medium effect size** is one that is greater than .3 but not more than .5; and c) A **large effect size** is greater than .5.

Cohen (1977; 1988, p. 222) states that the value computed for a **contingency coefficient** can be converted into the **w index** through use of the following equation: $w = \sqrt{C^2/(1 - C^2)}$. When the computed value $C = .29$ is substituted in the latter equation, the resulting value is $w = \sqrt{(.29)^2/[1 - (.29)^2]} = .30$. Employing Cohen's (1977, 1988) criteria for the **w index**, the value .30 is at the lower limit for a medium effect size. Since the maximum value the **contingency coefficient** can attain is 1, and in the case of a 2×2 contingency table the maximum value C can attain is .71, one can argue that in lieu of C , C_{adj} should be employed in computing w . If $C_{adj} = .41$ is employed to compute w , the value $w = \sqrt{(.41)^2/[1 - (.41)^2]} = .45$ is obtained, which based on Cohen's (1977, 1988) criteria still falls within the limits of a medium effect size.

Test 16g: The phi coefficient The **phi coefficient** (represented by the notation ϕ , which is the lower case Greek letter **phi**) is a measure of association that can only be employed with a 2×2 contingency table. The **phi coefficient** (which is discussed further in Section VII of the **Pearson product-moment correlation coefficient**) is, in actuality, a special case of the latter correlation coefficient. Specifically, it is a **Pearson product-moment correlation coefficient** that is computed if the values 0 and 1 are employed to represent the levels of two dichotomous variables. Although the value of **phi** can fall within the range -1 to $+1$, the latter statement must be qualified, since the lower and upper limits of **phi** are dependent on certain conditions. Carroll (1961) and Guilford (1965) note that in order for **phi** to equal -1 or $+1$, the following two conditions must be met with respect to the 2×2 contingency table described by the model in Table 16.6: $(a + b) = (c + d)$ and $(a + c) = (b + d)$.

Employing the notation in Table 16.6 for a 2×2 contingency table, the value of **phi** is computed with Equation 16.17.

$$\phi = \frac{ad - bc}{\sqrt{(a + b)(c + d)(a + c)(b + d)}} \quad (\text{Equation 16.17})$$

Since $\phi^2 = \chi^2/n$, many sources compute the value of **phi** through use of Equation 16.18 (which can be derived from the equation $\phi^2 = \chi^2/n$). Note that the result of Equation 16.18 will always be the absolute value of **phi** derived with Equation 16.17.²¹

$$\phi = \sqrt{\frac{\chi^2}{n}} \quad (\text{Equation 16.18})$$

Employing Equation 16.17, the value $\phi = -.30$ is computed below for Examples 16.1/16.2 (it will yield the same value for the data in Table 16.21).

$$\phi = \frac{(30)(40) - (70)(60)}{\sqrt{(30 + 70)(60 + 40)(30 + 60)(70 + 40)}} = -.30$$

If Equation 16.18 is employed, the absolute value of **phi** is computed to be $\phi = \sqrt{18.18/200} = .30$. As noted in the introductory remarks on measures of association, the computed absolute value $\phi = .30$ will be statistically significant at both the .05 and .01 levels, since the computed value $\chi^2 = 18.18$ is significant at the aforementioned levels of significance. Thus, one can conclude that in the underlying population the **phi** coefficient between the two variables is some value other than zero.²² In addition to the nondirectional alternative hypothesis being supported, the directional alternative hypothesis that is consistent with the data is also supported. This is the case since the computed value of chi-square is significant at the .10 and .02 levels (i.e., the obtained value $\chi^2 = 18.18$ is greater than $\chi^2_{.90} = 2.71$ and $\chi^2_{.98} = 5.41$).

It turns out the absolute value $\phi = .30$ computed for Examples 16.1/16.2 is almost identical to $C = .29$, the value of the **contingency coefficient** computed for same set of data. As a general rule, although the two values will not be identical, the absolute value of **phi** and the **contingency coefficient** will be close to one another.

Cohen (1977; 1988, p. 223) notes that **phi** is identical in value to the **w index** discussed in the previous section. Thus, Cohen (1977, 1988) has proposed the following (admittedly arbitrary) **phi** values as criteria for identifying the magnitude of an effect size (which are identical to the criteria stated earlier for the **w index**): **small effect size**: $.10 \leq \phi < .30$; **medium effect size**: $.30 \leq \phi < .50$; **large effect size**: $\phi \geq .50$. Employing Cohen's (1977, 1988) guidelines, the observed effect size for Examples 16.1/16.2 ($\phi = .30$) is at the lower limit of a medium effect size — i.e., there is a moderate relationship between the two variables employed in the study.

The use of the **phi coefficient** is most commonly endorsed in the case of 2×2 contingency tables involving two variables that are dichotomous in nature. Because of this, among others, Guilford (1965) and Fleiss (1981) note that one of the most useful applications of **phi** is for determining the intercorrelation between the responses of subjects on two dichotomous test items.²³ Siegel and Castellan (1988) note that when the two variables being correlated are ordered variables, computation of the **phi** coefficient sacrifices information, and because of this under such conditions it is preferable to employ alternative measures of association that are designed for ordered tables (such as **Goodman and Kruskal's gamma** which is discussed later in the book). For a more thorough overview of the **phi coefficient**, the reader should consult Guilford (1965) and Fleiss (1981), who, among other things, discuss various sources who argue in favor of employing measures other than **phi** with 2×2 tables.

Test 16h: Cramér's phi coefficient Developed by Cramér (1946), **Cramér's phi coefficient** (which will be represented by the notation ϕ_C) is an extension of the **phi coefficient** to contingency tables that are larger than 2×2 tables. **Cramér's phi coefficient**, which can assume a value between 0 and +1, is computed with Equation 16.19.

$$\phi_C = \sqrt{\frac{\chi^2}{n(k - 1)}} \quad \text{(Equation 16.19)}$$

Where: k represents the smaller of the two values of r and c in the contingency table

The derivation of **Cramér's phi coefficient** is based on the fact that the maximum value chi-square can attain for a set of data is $\chi_{\max}^2 = n(k - 1)$. Thus, the value ϕ_C is the square root of a proportion that represents the computed value of chi-square divided by the maximum possible chi-square value for a set of data. When the computed chi-square value for a set of data equals χ_{\max}^2 , the value $\phi_C = 1$ will be obtained, which indicates maximum dependency between the two variables.

Since for 2×2 tables **Cramér's phi** and the **phi coefficient** are equivalent (i.e., when $k = 2$, $\phi_C = \phi = \sqrt{\chi^2/n}$), they will both yield the absolute value of .30 for Examples 16.1/16.2. **Cramér's phi** is computed below for the 4×3 contingency table presented in Example 16.5. Since $c = 3$ is less than $r = 4$, $k = c = 3$.

$$\phi_C = \sqrt{\frac{59.16}{(280)(3 - 1)}} = .325$$

The computed value $\phi_C = .325$ is significant at both the .05 and .01 levels, since the computed value $\chi^2 = 59.16$ is significant at the aforementioned levels of significance. Thus, one

can conclude that in the underlying population, the value of **Cramér's phi coefficient** is some value other than zero.

Cohen (1977; 1988, p. 223) states that the value computed for **Cramér's phi coefficient** can be converted into the previously discussed **w index** through use of the following equation: $w = \phi_C \sqrt{k - 1}$. When the computed value $\phi_C = .325$ is substituted in the latter equation, the resulting value is $w = (.325)\sqrt{3 - 1} = .46$. Employing Cohen's (1977, 1988) criteria for the **w index**, the value $w = .46$ falls within the upper region of the range of values listed for a medium effect size.

Daniel (1990) notes that when a contingency table is square (i.e., $r = c$) and $\phi_C = 1$, there is a perfect correlation between the two variables (which will be reflected by the fact that all of the observations will be in the cells of one of the diagonals of the table). When $r \neq c$ and $\phi_C = 1$, however, the two variables will not be perfectly correlated in the same manner as is the case with a square contingency table. Conover (1980, 1999) notes that although under all conditions the possible range of values for ϕ_C will be between 0 and +1, its interpretation will depend on the values of r and c . He states that there is a tendency for the value of χ^2 (and consequently the value of ϕ_C) to increase as the values of r and c become larger. For this reason Conover (1980, 1999) suggests that ϕ_C may not be completely accurate for comparing the degree of association in different size tables. Daniel (1990) notes that when $r = c = 2$, the value of ϕ_C is equal to the square of the tie-adjusted value of **Kendall's tau (Test 30)** (discussed later in the book) computed for the same set of data. As is the case with the **phi coefficient**, when ordered categories are employed for both variables, sources do not recommend employing **Cramér's phi** since it sacrifices information. In designs involving variables with ordered categories, it is preferable to employ an alternative measure of association such as **Goodman and Kruskal's gamma**.

Test 16i: Yule's Q **Yule's Q** (Yule (1900)) is a measure of association for a 2×2 contingency table. It is presented in this section to illustrate that if two or more measures of association are computed for the same set of data, they may not yield comparable values. Since it employs less information than the **phi coefficient**, **Yule's Q** is less frequently recommended than **phi** as a measure of association for 2×2 tables. **Yule's Q** is actually a special case of **Goodman and Kruskal's gamma** (although unlike **gamma**, which is only used with ordered contingency tables, **Yule's Q** can be used for both ordered and unordered tables).

Employing the notation in [Table 16.6](#) for a 2×2 contingency table, Equation 16.20 is employed to compute the value of **Yule's Q**.

$$Q = \frac{ad - bc}{ad + bc} \quad \text{(Equation 16.20)}$$

Sources that discuss **Yule's Q** generally note that it tends to inflate the degree of association in the underlying population. Ott *et al.* (1992) note that an additional limitation is that if the absolute value of Q equals 1, it does not necessarily mean there is a perfect association between the two variables. In point of fact, if the observed frequency of any of the four cells in a 2×2 contingency table equals 0, the value of **Yule's Q** will equal either -1 or $+1$. For this reason, the meaning of Q can be quite misleading in cases where the frequency of one of the cells is equal to 0. Because of the latter, it is not recommended that **Yule's Q** be employed when there is a small number of frequencies in any of the four cells of a 2×2 contingency table.

Employing Equation 16.20, the value $Q = -.56$ is computed for Examples 16.1/16.2 (as well as for the data in [Table 16.21](#)).

$$Q = \frac{(30)(40) - (70)(60)}{(30)(40) + (70)(60)} = -.56$$

Note that although both the values of Q and **phi** suggest the presence of a negative association between the two variables, the absolute value $Q = .56$ is almost twice the value $\phi = .30$ computed previously for the same set of data. When Cohen's (1977, 1988) criteria are applied to the computed value of **phi** it indicates the presence of a medium effect size, yet if the same criteria are applied to $Q = .56$, it suggests the presence of a large effect size. (It should be noted, however, that Cohen does not endorse the use of the values he lists for **phi** with **Yule's Q**.)

Ott *et al.* (1992) note that the significance of **Yule's Q** can be evaluated with Equation 16.21.²⁴

$$z = \frac{Q}{\sqrt{\frac{1}{4}(1 - Q^2)^2 \left[\frac{1}{a} + \frac{1}{b} + \frac{1}{c} + \frac{1}{d} \right]}} \quad (\text{Equation 16.21})$$

Employing Equation 16.21 with the data for Examples 16.1/16.2, the value $z = -5.46$ is computed.

$$z = \frac{-.56}{\sqrt{\left[\frac{1}{4} \right] [1 - (.56)^2]^2 \left[\frac{1}{30} + \frac{1}{70} + \frac{1}{60} + \frac{1}{40} \right]}} = -5.46$$

The obtained value $z = -5.46$ is evaluated with **Table A1**. Since the obtained absolute value $z = 5.46$ is greater than the tabled critical two-tailed .05 and .01 values $z_{.05} = 1.96$ and $z_{.01} = 2.58$, the nondirectional alternative hypothesis is supported at both the .05 and .01 levels. Since $z = 5.46$ is greater than the tabled critical one-tailed .05 and .01 values $z_{.05} = 1.65$ and $z_{.01} = 2.33$, the directional alternative hypothesis that is consistent with the data is also supported at both the .05 and .01 levels.

Test 16j: The odds ratio (and the concept of relative risk) As is the case with **Yule's Q** (but unlike C , ϕ , and ϕ_c), the **odds ratio** (which is attributed to Cornfield (1951)) is a measure of association employed with contingency tables that is not a function of chi-square. Although the **odds ratio**, which will be represented by the notation o , can be applied to any size contingency table, it is easiest to interpret in the case of 2×2 tables. The **odds ratio** expresses the degree of association between the two variables in a different numerical format than all of the previously discussed measures of association. In some respects it provides a more straightforward way of interpreting the results of a contingency table than the correlational measures of association discussed previously.

The **odds ratio** is one of two measures that are commonly employed in epidemiological research to indicate the risk of a person contracting a disease. Although **relative risk**, which is the second of the two measures, is intuitively easier to understand, the **odds ratio** is more useful when employed within the context of statistical analysis. In this section both of the aforementioned measures will be examined. In order to do this, consider the data in **Table 16.23**. We will assume that the latter table represents the results of a hypothetical study which evaluates if someone who washes her hands immediately after handling a diseased animal is less likely to contract the disease than someone who does not wash her hands.

Note that **Table 16.23** is identical to **Table 16.2**, except for the following: a) In the case of the row variable, the **noise** condition has been replaced by a **washes hands** condition, and the **no**

noise condition has been replaced by a **does not wash** condition; b) In the case of the column variable, the **helped the confederate** response category has been replaced by the **contracts the disease** category, and the **did not help the confederate** response category has been replaced by the **does not contract the disease** category. Thus, the **independent variable** in the study summarized in Table 16.23 is **whether or not a person washes her hands**, and the **dependent variable** is **whether or not the person contracts the disease**.

Table 16.23 Summary of Hand Washing Study

	Contracts the disease	Does not contract the disease	Row sums
Washes hands	30	70	100
Does not wash	60	40	100
Column sums	90	110	Total observations 200

Relative risk allows a researcher to compare the relative probabilities of contracting a disease. Specifically, **relative risk** is the probability of contracting a disease if you are a member of one group (typically the group that is considered to have the higher risk) divided by the probability of contracting the disease if you are a member of the other group (typically the group that is considered to have the lower risk). In the case of our example, the probability of contracting the disease in the **does not wash** group (which will be considered the high risk group) is $60/100 = .6$. The latter probability is simply the number of people in the **does not wash** group who **contract the disease** (60) divided by the total number of people who constitute the **does not wash** group (100). In the same respect, the probability of contracting the disease in the **washes hands** group (which will be considered the low risk group) is $30/100 = .3$. The latter probability is simply the number of people in the **washes hands** group who **contract the disease** (30) divided by the total number of people who constitute the **washes hands** group (100). Through use of the notation in Table 16.6, the above can be expressed as follows.

$$p(\text{Contracts disease}/\text{Does not wash}) = c/(c + d)$$

$$p(\text{Contracts disease}/\text{Washes hands}) = a/(a + b)$$

The relative risk (*RR*) is computed with Equation 16.22.

(Equation 16.22)

$$RR = \frac{c/(c + d)}{a/(a + b)} = \frac{60/(60 + 40)}{30/(30 + 70)} = 2$$

or

$$RR = \frac{ac + bc}{ac + ad} = \frac{(30)(60) + (70)(60)}{(30)(60) + (30)(40)} = 2$$

The value $RR = 2$ computed for **relative risk** means that a person who does not wash her hands is 2 times more likely to contract the disease than a person who washes her hands. If the numerator and denominator of Equation 16.22 are reversed (which computes the relative risk for someone who washes relative to someone who does not wash), the value $RR = .5$ is computed. The value $RR = .5$ indicates that a person who washes her hands has half (.5) the likelihood of contracting the disease than a person who does not wash her hands.

If we apply the computations for **relative risk** to the variables employed in Example 16.1, we can state that someone in the **no noise** condition is 2 times more likely to **help the confederate** than someone in the **noise** condition.

At this point we will turn our attention to the **odds ratio**. Before considering the latter measure it will be useful to clarify the concept of **odds**. The odds that an event (to be designated X) will occur are computed by dividing the probability that the event will occur by the probability that the event will not occur. The latter is described by Equation 16.23.

$$\text{Odds}(X) = \frac{p(X \text{ will occur})}{p(X \text{ will not occur})} \quad (\text{Equation 16.23})$$

The following should be noted with respect to **odds**: a) The computed value for odds can fall anywhere in the range 0 to infinity; b) When the value computed for odds is greater than 1, it indicates that the probability of an event occurring is better than one-half (1/2). Thus, the larger the odds of an event occurring, the higher the probability that the event will occur; c) When the value computed for odds is less than 1, it indicates that the probability of an event occurring is less than one-half (1/2). Thus, the smaller the odds of an event occurring, the lower the probability that the event will occur. The lowest value that can be computed for odds is 0, which indicates that the probability the event will occur is 0; d) When the value computed for odds equals 1, it indicates that the probability of the event occurring is one half (1/2) — i.e., there is a 50-50 chance of the event occurring; and e) More often than not, when odds are published in the media they are the odds that an event will not occur rather than the odds that the event will occur. As an example, if the bookmakers' odds of a horse winning the Kentucky Derby are 4 to 1, it indicates that the bookmakers are saying there is only a .2 probability the horse will win the derby, and a .8 probability the horse will not win. Consequently, the odds of the horse not winning the derby are computed as follows: $p(\text{Will not win})/p(\text{Will win}) = .8/.2 = 4$, which is generally expressed as odds of 4 to 1 (often written as 4:1). If in the opinion of the bookmakers the likelihood that a horse will win the derby is 2 out of 5, then the odds are computed by dividing the likelihood the horse won't win (3/5) by the likelihood the horse will win (2/5), which is 3/2 (or 1.5). The latter odds are expressed as 1.5 to 1 (or 1.5:1) or more commonly as 3 to 2 (or 3:2).²⁵

Odds will now be computed for the data in [Tables 16.2/16.23](#).

$$\text{Odds}(\text{Help}/\text{No noise}) = \frac{p(\text{Help}/\text{No noise})}{p(\text{Not help}/\text{No noise})} = \frac{60/100}{40/100} = 1.5$$

$$\text{Odds}(\text{Help}/\text{Noise}) = \frac{p(\text{Help}/\text{Noise})}{p(\text{Not help}/\text{Noise})} = \frac{30/100}{70/100} = .429$$

$$\begin{aligned} \text{Odds}(\text{Contracts disease}/\text{Does not wash}) &= \frac{p(\text{Contracts disease}/\text{Does not wash})}{p(\text{Does not contract disease}/\text{Does not wash})} \\ &= \frac{60/100}{40/100} = 1.5 \end{aligned}$$

$$\begin{aligned} \text{Odds}(\text{Contracts disease}/\text{Washes hands}) &= \frac{p(\text{Contracts disease}/\text{Washes hands})}{p(\text{Does not contract disease}/\text{Washes hands})} \\ &= \frac{30/100}{70/100} = .429 \end{aligned}$$

The above results indicate that the odds of **helping** in the **no noise** condition are 1.5 to 1. Since the value 1.5 is greater than 1, it indicates the probability of a subject **helping** in the **no noise** condition is greater than 1/2. The odds of **helping** in the **noise** condition are .429 to 1. Since the value .429 is less than 1, it indicates the probability of a subject **helping** in the **noise** condition is less than 1/2. In the same respect the odds of **contracting the disease** in the **does not wash** condition are 1.5 to 1, while the odds of **contracting the disease** in the **washes hands** condition are .429 to 1.

The **odds ratio** is simply the ratio between the two odds computed for a contingency table. Typically the larger number is divided by the smaller number. Thus $o = 1.5/.429 = 3.5$. In the case of Example 16.1, the latter value indicates that the odds of **helping** in the **no noise** condition are 3.5 times larger than the odds of **helping** in the **noise** condition. In the case of the data in Table 16.23, the value $o = 3.5$ indicates that the odds of **contracting the disease** in the **does not wash** condition are 3.5 times larger than the odds of **contracting the disease** in the **washes hands** condition.²⁶

It can be algebraically demonstrated that Equation 16.24 (which employs the notation in Table 16.6) provides a simple method for computing the **odds ratio** for a 2×2 contingency table. The latter equation is employed below to obtain the value $o = 3.5$ for our data.²⁷

$$o = \frac{bc}{ad} = \frac{(70)(60)}{(30)(40)} = 3.5 \quad \text{(Equation 16.24)}$$

Various sources (e.g., Pagano and Gauvreau (1993)) note that when the probability of an event occurring is very low, the values in cells *a* and *c* of Tables 16.6/16.23 will be very small. When the latter is true, the values computed for the **relative risk** and **odds ratio** will be very close together, since if the values of *a* and *c* equal 0, the equation $RR = (ac + bc)/(ac + ad)$ for computing relative risk reduces to Equation 16.24. Although the latter is not true for the example under discussion, a case where the **relative risk** and **odds ratio** are, in fact, almost identical is described in Section IX (the **Appendix**) of the **Pearson product-moment correlation coefficient** under the discussion of **meta-analysis and related topics**.

Although, as noted earlier, the **odds ratio** can be extended beyond 2×2 tables, it becomes more difficult to interpret with larger contingency tables. However, in instances where there are more than two rows but only two columns, its interpretation is still relatively straightforward. To illustrate, assume that in Example 16.1 we have three noise conditions instead of two — specifically, **loud noise**, **moderate noise**, and **no noise**. Table 16.24 depicts a hypothetical set of data that summarizes the results of such a study.

Table 16.24 Summary of Data for a 3×2 Contingency Table

	Helped the confederate	Did not help the confederate	Row sums
Loud noise	30	70	100
Moderate noise	50	50	100
No noise	80	20	100
Column sums	160	140	Total observations 300

Within any of the three noise conditions, we can determine the odds that someone in that condition will **help the confederate**. This is accomplished by dividing the proportion of subjects in a given condition who **helped the confederate** by the proportion of subjects in the condition who **did not help the confederate**. Thus, for the **loud noise** condition the odds that someone will

help the confederate are $(30/100)/(70/100) = .43$. For the **moderate noise** condition the odds that someone will **help the confederate** are $(50/100)/(50/100) = 1$. For the **no noise** condition the odds that someone will **help the confederate** are $(80/100)/(20/100) = 4$. From these values we can compute the following three odds ratios: a) The **odds ratio** of someone in the **no noise** condition **helping the confederate** versus someone in the **loud noise** condition: $o = 4/.43 = 9.3$; b) The **odds ratio** of someone in the **no noise** condition **helping the confederate** versus someone in the **moderate noise** condition: $o = 4/1 = 4$; and c) The **odds ratio** someone in the **moderate noise** condition **helping the confederate** versus someone in the **loud noise** condition: $o = 1/.43 = 2.33$.

Thus, the odds of someone in the **no noise** condition **helping the confederate** are 9.3 times larger than the odds of someone in the **loud noise** condition **helping the confederate**, and 4 times larger than the odds of someone in the **moderate noise** condition **helping the confederate**. The odds of someone in the **moderate noise** condition **helping the confederate** are 2.33 times larger than the odds of someone in the **loud noise** condition **helping the confederate**.

Test 16j-a: Test of significance for an odds ratio and computation of a confidence interval for an odds ratio Christensen (1990) and Pagano and Gauvreau (1993) note that Equation 16.25 can be employed to evaluate the null hypothesis that the true value of the **odds ratio** in the underlying population is equal to 1 (i.e., that the probability an event will occur is equal to the probability the event will not occur). Since the sampling distribution of the **odds ratio** is positively skewed, a logarithmic scale transformation is employed in computing the test statistic, which is a standard normal deviate (i.e., a z score). (Logarithmic scale transformations are discussed in Section VII of the ***t* test for two independent samples**.) Without the logarithmic transformation, the numerator of Equation 16.25 would be $(o - 1)$, where o is the computed value of the **odds ratio**, and 1 is the expected value of the **odds ratio** if the probabilities for the event occurring and not occurring are equal. By virtue of the logarithmic transformation, the numerator of Equation 16.25 becomes the natural logarithm (which is defined in Endnote 5 in the **Introduction**) of the **odds ratio** minus 0, which is the natural logarithm of 1.

$$z = \frac{\ln(o) - 0}{SE} \quad (\text{Equation 16.25})$$

Where: $\ln(o)$ represents natural logarithm of the computed value of the **odds ratio**
 SE represents the standard error, which is the estimated standard deviation of the sampling distribution. The standard error is computed as follows:²⁸

$$SE = \sqrt{\frac{1}{a} + \frac{1}{b} + \frac{1}{c} + \frac{1}{d}}$$

If we evaluate the null hypothesis regarding the **odds ratio** in reference to the data for Example 16.1, the following values are computed: a) Through use of the appropriate tables or a calculator (using the \ln key), the natural logarithm of the **odds ratio** ($o = 3.5$) is determined to be 1.2528; and b) The value of the standard error is computed to be $SE = .2988$.

$$SE = \sqrt{\frac{1}{30} + \frac{1}{70} + \frac{1}{60} + \frac{1}{40}} = .2988$$

Substituting the values $\ln(o) = 1.2528$ and $SE = .2988$ in Equation 16.25, the value $z = 4.19$ is computed.

$$z = \frac{1.2528 - 0}{.2988} = 4.19$$

The value $z = 4.19$ is evaluated with **Table A1** in the **Appendix**. In **Table A1** the tabled critical two-tailed .05 and .01 values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed .05 and .01 values are $z_{.05} = 1.65$ and $z_{.01} = 2.33$. If a nondirectional alternative hypothesis is employed, in order to reject the null hypothesis the absolute value of z must be equal to or greater than the tabled critical two-tailed value at the prespecified level of significance. If a directional alternative hypothesis is employed, in order to reject the null hypothesis the following must be true: a) The absolute value of z must be equal to or greater than the tabled critical one-tailed value at the prespecified level of significance; and b) If the alternative hypothesis stipulates that the population **odds ratio** is less than 1, the sign of the computed z value must be negative (since a positive number less than 1 will yield a negative value for a logarithm). If the alternative hypothesis stipulates that the underlying population **odds ratio** is greater than 1, the sign of the computed z value must be positive (since a number greater than 1 will yield a positive value for a logarithm). Since the computed value $z = 4.19$ is greater than the two-tailed .05 and .01 values $z_{.05} = 1.96$ and $z_{.01} = 2.58$, the nondirectional alternative hypothesis is supported at both the .05 and .01 levels. Since $z = 4.19$ is a positive number that is greater than the tabled critical one-tailed .05 and .01 values $z_{.05} = 1.65$ and $z_{.01} = 2.33$, the directional alternative hypothesis stipulating that the underlying population **odds ratio** is greater than 1 is supported at both the .05 and .01 levels. Thus, we can conclude that the population **odds ratio** is not equal to 1.

Christensen (1990) and Pagano and Gauvreau (1993) describe the computation of a confidence interval for the **odds ratio**. The latter computation initially requires that a product based on multiplying the standard error by the relevant z value for the confidence interval be obtained. Thus, if one is computing the 95% confidence interval, the standard error is multiplied by the tabled critical two-tailed .05 value $z_{.05} = 1.96$. If one is computing the 99% confidence interval, the standard error is multiplied by the tabled critical two-tailed .01 value $z_{.01} = 2.58$. The latter product for the desired confidence interval is then added to and subtracted from the natural logarithm of the odds ratio. The antilogarithms (which are the original numbers for which the logarithms were computed) of the resulting two values are determined. The latter values define the limits of the confidence interval.

To illustrate, the 95% confidence interval will be computed. We first multiply the standard error $SE = .2988$ by the tabled critical two-tailed .05 value $z_{.05} = 1.96$, and obtain $(.2988)(1.96) = .5856$. The latter value is added to and subtracted from the natural logarithm of the odds ratio, which was previously computed to be 1.2528. Thus $1.2528 \pm .5856$ yields the two values .6672 and 1.8384. Through use of the appropriate tables or a calculator (using the e^x key), the antilogarithms of the latter two values are determined to be 1.9488 and 6.2865. These values represent the limits that define the 95% confidence interval for the **odds ratio**. In other words, we can be 95% confident (or the probability is .95) that the true value of the odds ratio in the population falls between 1.9488 and 6.2865.

VII. Additional Discussion of the Chi-Square Test for $r \times c$ Tables

1. Simpson's paradox **Simpson's paradox** is where either the direction or magnitude of the relationship between two variables (to be designated X and Y) is influenced by a third variable (to be designated Z). When the relationship between X and Y is summarized in a two-dimensional contingency table, the direction and/or the magnitude of the relationship between the two

variables is different from what it appears to be when the data are summarized in a three-dimensional contingency table which takes into account all three variables.

To illustrate, let us assume that a study is conducted which evaluates the efficacy of two surgical treatments (to be designated Treatment A and Treatment B) for a seizure disorder. The study is conducted at two hospitals to be designated as Hospital 1 and Hospital 2. The neurosurgeons who perform the surgery in Hospital 1 are extremely experienced in using both of the surgical techniques. The neurosurgeons at Hospital 2, on the other hand, are relatively inexperienced in using the surgical procedures. However, the researcher who designs the study is unaware of differences in experience between the surgeons at the two hospitals. Consequently, the researcher conceptualizes the study as having one independent variable, which is the type of surgical treatment a patient receives. The dependent variable (which constitutes the second variable in the study) is the measure of the efficacy of the treatments — specifically, the categorization of a patient as a success or a failure. For purposes of illustration we will assume that 550 patients participate in the study, and that half of the patients receive Treatment A and the other half Treatment B. Of the 550 patients, 370 are treated at Hospital 1, and 180 are treated at Hospital 2. Table 16.25 summarizes the results of the study in the form of a 2 × 2 contingency table.

Table 16.25 Data for Neurosurgery Study in 2 × 2 Contingency Table

		Response to treatment		Totals
		Success	Failure	
Treatment	Treatment A	160	115	275
	Treatment B	160	115	275
Totals		320	230	550

It should be apparent from inspection of Table 16.25 that the two treatments yield the identical number of successes and failures, and thus there is no difference in the efficacy of the two treatments. The latter can be confirmed by the fact that if a **chi-square test for homogeneity** is employed to evaluate the data (without using the correction for continuity), it yields the value $\chi^2 = 0$ (since the expected and observed frequency for each cell will be equal). We can also make the following additional statements about the data: a) A patient has a $160/275 = .58$ probability of responding favorably to Treatment A, and a $160/275 = .58$ probability of responding favorably to Treatment B; b) If the **odds ratio** is computed (through use of Equation 16.24), the value $o = [(115)(160)]/[(160)(115)] = 1$ is computed. An **odds ratio** of 1 in reference to Table 16.25 indicates that the odds of Treatment A being successful are equal to the odds of Treatment B being successful.

Table 16.26 summarizes the results of the study in the format of a three-dimensional contingency table. Note that in addition to the two variables taken into account in Table 16.25, Table 16.26 includes as a third variable the hospital at which a patient received the treatment. Inspection of Table 16.26 reveals that if the hospital that administered the treatment is taken into account, one reaches a different conclusion regarding the efficacy of the two treatments.

Inspection of Table 16.26 reveals the following: a) In Hospital 1 a patient has a $120/145 = .83$ probability of having a successful response to Treatment B, but only a $150/225 = .67$ probability of having a successful response to Treatment A. If the **odds ratio** is computed for the Hospital 1 data, the value $o = [(75)(120)]/[(150)(25)] = 2.4$ is computed. The latter value indicates that the odds of Treatment B being successful are 2.4 times larger than the odds of Treatment A being successful. If a **chi-square test for homogeneity** is employed to evaluate the 2 × 2 table for Hospital 1, it yields the value $\chi^2 = 11.58$, which is significant at both the .05 and

Table 16.26 Data for Neurosurgery Study in Three-Dimensional Contingency Table

Treatment		Hospital 1		Hospital 2		Totals
		Success	Failure	Success	Failure	
Treatment	Treatment A	150	75	10	40	275
	Treatment B	120	25	40	90	275
Totals		270	100	50	130	550

.01 levels (since for $df = 1$, $\chi^2_{.05} = 3.84$ and $\chi^2_{.01} = 6.63$). The values computed in Hospital 1 clearly indicate that Treatment B is more successful than Treatment A; b) In Hospital 2 a patient has a $40/130 = .31$ probability of having a successful response to Treatment B, but only a $10/50 = .20$ probability of having a successful response to Treatment A. If the **odds ratio** is computed for the Hospital 2 data, the value $o = [(40)(40)]/[(10)(90)] = 1.78$ is computed. The latter value indicates that the odds of Treatment B being successful are 1.78 times larger than the odds of Treatment A being successful. If a **chi-square test for homogeneity** is employed to evaluate the 2×2 table for Hospital 2, it yields the value $\chi^2 = 2.09$ (which is not significant, since $\chi^2 = 2.09$ is less than $\chi^2_{.05} = 3.84$).²⁹ The fact remains, however, that the success rate in Hospital 2 for Treatment B is higher than it is for Treatment A. The lack of a significant result for the Hospital 2 data may be a function of the relatively small sample size, which limits the power of the analysis. Thus, there is a suggestion that Treatment B may also be more successful than Treatment A in Hospital 2.

Analysis of the treatments within each of the two hospitals strongly suggests that Treatment B is more successful than Treatment A. Yet when the data are pooled and expressed within the format of a 2×2 contingency table, there is no apparent difference between the two treatments. This is a classic example of **Simpson's paradox**, in that both the magnitude and direction of the relationship between two variables (the type of treatment administered and a patient's response to the treatment) is influenced by a third variable (the hospital at which a treatment was administered). The fact that the success rate for both of the treatments is higher in Hospital 1 than it is in Hospital 2, reflects the fact that the doctors at Hospital 1 are more skilled in using the surgical treatments than the doctors at Hospital 2 (although there is the possibility that the lower success rate at Hospital 2 could be due to the fact that a disproportionate number of the more difficult cases were treated at that hospital). The superiority of Treatment B over Treatment A is masked in Table 16.25, because the latter table inappropriately weights the outcomes at the different hospitals. The two factors that are responsible for the inappropriate weighting are: a) In Hospital 1 fewer patients received Treatment B than Treatment A, while in Hospital 2 a greater number of patients received Treatment B than Treatment A; and b) The doctors at Hospital 1 are more experienced (and thus probably more successful in conducting the surgery) than the doctors at Hospital 2. The joint influence of these two factors is what is responsible for the absence of any apparent differences between the two treatments when the data are summarized in a 2×2 contingency table (i.e., Table 16.25). Thus, **Simpson's paradox** illustrates that when data based on three variables (typically two independent variables and one dependent variable) are collapsed into a 2×2 table, it can dramatically distort what really occurred in a study.

2. Analysis of multidimensional contingency tables A multidimensional contingency table is one that contains information on three or more variables (such as Table 16.26). Although the **chi-square test for $r \times c$ tables** can be generalized for use with multidimensional tables, two commonly employed alternative approaches for evaluating multidimensional tables are the **log-likelihood ratio** (which employs a statistic commonly designated by the notation G), and **log-**

linear analysis. As is the case with the tests that have been described which employ the chi-square distribution (i.e., the **chi-square goodness-of-fit test** and the **chi-square test for $r \times c$ tables**), both of the aforementioned methods can also be employed for the analysis of one- and two-dimensional tables. When the different methods for evaluating contingency tables are employed with the same set of data, they generally yield similar results.

The analysis of multidimensional contingency tables shares a number of things in common with the analysis of **factorial designs** with an **analysis of variance**, (factorial designs are discussed under the **between-subjects factorial analysis of variance (Test 27)**). Both of the aforementioned analyses can be employed to evaluate data where there are two or more independent variables and a dependent variable. In designs in which there are multiple independent variables, within the framework of conducting an omnibus test on the complete body of data, it is necessary to determine whether there are any **interactions** present. An **interaction** is present in a set of data when the performance of subjects on one independent variable is not consistent across all the levels of another independent variable. In the case of multidimensional contingency tables, the concept of interaction can also be generalized to designs where no clear distinction is made with respect to whether variables are independent or dependent variables. Although the concept of interaction will be discussed in this section, a more thorough discussion of it can be found in Section V of the **between-subjects factorial analysis of variance**.

The analysis of multidimensional contingency tables is a complex topic, and a full discussion of it is beyond the scope of this book. In this section I will limit my discussion of the topic to the generalization of the **chi-square test for $r \times c$ tables** to multidimensional tables. Specifically, the latter test will be generalized in order to evaluate a three-dimensional contingency table. The reader should keep in mind that the multidimensional contingency table to be evaluated in this section will represent an example of the simplest multidimensional table that can be constructed — a table with three variables, with each variable being comprised of two levels. As the number of variables (as well as the number of levels/categories per variable) increase, the analysis of a multidimensional table becomes increasingly complex. In addition, the more variables that are included in a study, the more difficult it becomes to obtain a clear interpretation of the results of any analyses that are conducted.

As noted earlier, it is possible to have a three-dimensional table that summarizes the data for two independent variables and a dependent variable.³⁰ Example 16.6 (which is similar to Example 16.1, except for the fact that it has a second independent variable) will result in a multidimensional table of this type. It was also noted that it is possible to have a three-dimensional table where no clear-cut distinction is made between the independent and dependent variables. Example 16.7 (which is similar to Example 16.2, except for the fact that it describes a study involving three variables instead of two variables) will result in a multidimensional table of this type. Examples 16.6 and 16.7 will be employed to illustrate the generalization of the **chi-square test for $r \times c$ tables** to a three-dimensional contingency table.

Example 16.6 *A researcher conducts a study on altruistic behavior. All subjects who participate in the experiment are males. Each of the 160 male subjects is given a one-hour test which is ostensibly a measure of intelligence. During the test the 65 subjects are exposed to continual loud noise, which they are told is due to a malfunctioning generator. Another 95 subjects are not exposed to any noise during the test. Upon completion of this stage of the experiment, each subject on leaving the room is confronted by a middle-aged man or woman whose arm is in a sling. The latter individual asks the subject if he would be willing to help him/her carry a heavy package to his/her car. 80 of the subjects are confronted by a male who asks for help, while the other 80 are confronted by a female. In actuality, the person requesting help is an experimental confederate (i.e., working for the experimenter). The dependent variable in the*

experiment is whether or not a subject helps the person carry the package. Table 16.27 summarizes the data for the experiment. Do the data indicate that altruistic behavior is influenced by noise and/or the gender of the person requesting help?

Example 16.7 A researcher wants to determine if there is a relationship between the following three variables/dimensions: a) A person’s political affiliation — specifically, whether a person is a Democrat or a Republican; b) A person’s categorization on the personality dimension of introversion–extroversion; and c) A person’s gender (male versus female). One hundred and sixty people are recruited to participate in the study. All of the subjects are given a personality test, on the basis of which each subject is classified as an introvert or an extrovert. Each subject is then asked to indicate whether he or she is a Democrat or a Republican. The data for Example 16.7, which can be summarized in the form of a three-dimensional contingency table, are presented in Table 16.27. Do the data indicate that the three variables are independent of one another?

Table 16.27 is a three-dimensional contingency table that simultaneously summarizes the data for Examples 16.6 and 16.7. In a three-dimensional table, one of the variables is designated as the **row** variable, a second variable is designated as the **column** variable, and the third variable is designated as the **layer** variable. (Zar (1999) employs the term **tier** variable to designate the third variable.) In a three-dimension table there will be a total of $r \times c \times l$ cells, where r represents the number of row categories, c the number of column categories, and l the number of layer categories.

As noted above, the experiment described in Example 16.6 has two independent variables. One of the independent variables is the **noise manipulation**, which is comprised of the two levels **noise** versus **no noise**. In Table 16.27 the **noise manipulation** independent variable is designated as the **row variable**. The second independent variable is whether a subject is confronted by a **male** or a **female** confederate. In Table 16.27 the independent variable represented by the **gender of the confederate** is designated as the **column variable**. The dependent variable is whether or not a subject **helped the confederate**. In Table 16.27 **whether or not a subject helped**, which has the two levels **helped** and **did not help**, is designated as the **layer variable**.

In the case of Example 16.7, where no clear-cut distinction is made with respect to a variable being an independent or dependent variable, the **row variable** will be the categorization of a person on the **introversion-extroversion dimension**, the **column variable** will be the **gender of the subject (male-female)**, and the **layer variable** will be a person’s **political affiliation (Democrat-Republican)**.

Table 16.27 Summary Data for Examples 16.6/16.7

	Helped/Democrat		Did not help/Republican		Totals
	Male	Female	Male	Female	
Noise/Introvert	10	15	25	15	65
No Noise/Extrovert	25	45	20	5	95
Totals	35	60	45	20	160
Sums:	Row 1 (Noise/Introvert)		$= O_{1..} = R_1 = 65$		
	Row 2 (No Noise/Extrovert)		$= O_{2..} = R_2 = 95$		
	Column 1 (Male)		$= O_{.1.} = C_1 = 80$		
	Column 2 (Female)		$= O_{.2.} = C_2 = 80$		
	Layer 1 (Helped/Democrat)		$= O_{..1} = L_1 = 95$		
	Layer 2 (Did not help/Republican)		$= O_{..2} = L_2 = 65$		

Christensen (1990, pp. 63–64) notes that among the possible ways of conceptualizing the relationship between the variables in a three-way contingency table are the following: a) Rows, columns, and layers are all independent of one another; b) Rows are independent of columns and layers (with columns and layers not necessarily being independent of one another); c) Columns are independent of rows and layers (with rows and layers not necessarily being independent of one another); d) Layers are independent of rows and columns (with rows and columns not necessarily being independent of one another); e) Given any specific level of a row, columns and layers are independent of one another; f) Given any specific level of a column, rows and layers are independent of one another; g) Given any specific level of a layer, rows and columns are independent of one another.

Each of the aforementioned ways of conceptualizing a contingency table is often referred to as a **model**. Of the seven models noted above, **Model a** is referred to as the **model of complete (or mutual) independence**, **Models b, c, and d** as **models of partial independence**, and **Models e, f, and g** as **models of conditional independence**. The discussion to follow will be limited to a description of the analysis of the models of **complete** and **partial independence**.

Test of model of complete independence The initial analysis that will be conducted on [Table 16.27](#) will evaluate whether in each of the studies all three variables are independent of one another. This analysis (which, as noted earlier, assesses **complete independence**), will be evaluated with what will be referred to as the **omnibus chi-square analysis**. Within the framework of the latter analysis, the following null and alternative hypotheses will be evaluated.

Null hypothesis H_0 : In Example 16.6, in the underlying population the three variables (exposure to noise, gender of confederate, and helping behavior) are all independent of one another. In Example 16.7, in the underlying population the three variables (introversion–extroversion, gender, and political affiliation) are all independent of one another. The notation $H_0: o_{ijk} = e_{ijk}$ for all cells can also be employed, which means that in the underlying population(s) the sample(s) represent(s), for each of the $r \times c \times l$ cells the observed frequency of a cell is equal to the expected frequency of the cell. With respect to the sample data, this translates into the observed frequency of each of the $r \times c \times l$ cells being equal to the expected frequency of the cell.

Alternative hypothesis H_1 : In Example 16.6, in the underlying population the three variables (exposure to noise, gender of confederate, and helping behavior) are not all independent of one another. In Example 16.7, in the underlying population the three variables (introversion–extroversion, gender, and political affiliation) are not all independent of one another. The notation $H_1: o_{ijk} \neq e_{ijk}$ for at least one cell can also be employed, which means that in the underlying population(s) the sample(s) represent(s), for at least one of the $r \times c \times l$ cells the observed frequency of a cell is not equal to the expected frequency of the cell. With respect to the sample data, this translates into the observed frequency of at least one of the $r \times c \times l$ cells not being equal to the expected frequency of the cell. It will be assumed that the alternative hypothesis is nondirectional (although it is possible to have a directional alternative hypothesis).

Equation 16.26 (which is a generalization of Equation 16.2 to a three-dimensional table) is employed to compute the test statistic for a three-dimensional table.

$$\chi^2 = \sum_{i=1}^r \sum_{j=1}^c \sum_{k=1}^l \left[\frac{(O_{ijk} - E_{ijk})^2}{E_{ijk}} \right] \quad (\text{Equation 16.26})$$

Note that the notation k in the ijk subscript for the observed and expected frequencies in Equation 16.26 (as well as in the null and alternative hypotheses) represents the k^{th} layer of the layer variable. Thus, in Equation 16.26 the notation E_{ijk} means the expected frequency for the cell in Row i , Column j , and Layer k . Note that just as there are r levels on the row variable and c levels on the column variable, there are l levels on the layer variable.

The operations described by Equation 16.26 (which are the same as those described for computing the chi-square statistic for the **chi-square goodness-of-fit test** and the **chi-square test for $r \times c$ tables**) are as follows: a) The expected frequency of each cell is subtracted from its observed frequency; b) For each cell, the difference between the observed and expected frequency is squared; c) For each cell, the squared difference between the observed and expected frequency is divided by the expected frequency of the cell; and d) The value of chi-square is computed by summing all of the values computed in part c).

Note that in contrast to Equation 16.26, there is only one summation sign in the analogous equation for the **chi-square goodness-of-fit test** (Equation 8.2), since the latter test has only a single variable (designated as the row variable). In the same respect there are two summation signs for the analogous equation for the **chi-square test for $r \times c$ tables** (Equation 16.2), since the latter test has two variables — a row variable and a column variable. Since there are three variables, the three-dimensional equation requires summing over all three dimensions. (If there are four dimensions the chi-square equation will have four summation signs, since summing will have to be done over all four dimensions. Five dimensions will require five summation signs, and so on.)

The protocol for conducting the chi-square analysis is identical to that employed for a two-dimensional table. The only aspect of the analysis that is different is the computation of the expected frequency of a cell, which in the case of a three-dimensional table is computed with Equation 16.27. Note that Equation 16.27 is written two ways. The first representation of the equation is consistent with the format used in Equation 16.1, the equation for computing the expected frequency of a two-dimensional table. Thus, $O_{i..}$ represents the number of observations in the i^{th} row, which can be represented more simply as R_i . $O_{.j.}$ represents the number of observations in the j^{th} column, which can be represented more simply as C_j . $O_{..k}$ represents the number of observations in the k^{th} layer, which can be represented more simply as L_k . The totals for the rows, column, and layers are recorded at the bottom of [Table 16.27](#).

$$E_{ijk} = \frac{O_{i..} O_{.j.} O_{..k}}{n^2} = \frac{R_i C_j L_k}{n^2} \quad (\text{Equation 16.27})$$

The notation in Equation 16.27 indicates that to compute the expected frequency of a cell, the observed frequency of row the cell is in is multiplied by the observed frequency of the column the cell is in, and the resulting value is multiplied by the observed frequency of the layer the cell is in. The resulting product is divided by the square of the total number of observations in the contingency table.

To illustrate, we will compute the expected frequency for the cell in the upper left of [Table 16.27](#). The latter cell, which is Cell₁₁₁ (i.e., the cell in Row 1, Column 1, and Layer 1), represents subjects in the **noise/introvert** category, the **male** category, and the **helped/Democrat** category. We thus multiply the total number of observations in Row 1 (which is 65) by the total number of observations in Column 1 (which is 80) by the total number of observations in Layer 1 (which is 95). The product is divided by the square of the total number of observations in the contingency table (the total number of observations being 160). Thus: $E_{111} = [(65)(80)(95)]/(160)^2 = 19.30$. The expected frequencies of the remaining seven cells are computed below.

$$\begin{aligned}
E_{121} &= [(65)(80)(95)]/(160)^2 = 19.30 \\
E_{112} &= [(65)(80)(65)]/(160)^2 = 13.20 \\
E_{122} &= [(65)(80)(65)]/(160)^2 = 13.20 \\
E_{211} &= [(95)(80)(95)]/(160)^2 = 28.20 \\
E_{221} &= [(95)(80)(95)]/(160)^2 = 28.20 \\
E_{212} &= [(95)(80)(65)]/(160)^2 = 19.30 \\
E_{222} &= [(95)(80)(65)]/(160)^2 = 19.30
\end{aligned}$$

The chi-square analysis from this point on is identical to that employed for a two-dimensional table. The analysis is summarized in [Table 16.28](#). The cell identification codes in the table are **N/I** = Noise/Introvert; **NN/E** = No noise/Extrovert; **M** = Male; **F** = Female; **H/D** = Helped/Democrat; **DNH/R** = Did not help/Republican.

The degrees of freedom employed in the omnibus analysis of a three-dimensional contingency table are $df = rcl - r - c - l + 2$.³¹ Thus, for our example, since $r = c = l = 2$, $df = (2)(2)(2) - 2 - 2 - 2 + 2 = 4$. Employing [Table A4](#), the tabled critical .05 and .01 chi-square values for $df = 4$ are $\chi^2_{.05} = 9.49$ and $\chi^2_{.01} = 13.28$. Since the computed value $\chi^2 = 37.24$ is greater than both of the aforementioned critical values, the null hypothesis can be rejected at both the .05 and .01 levels. By virtue of rejecting the null hypothesis, the researcher can conclude that in Examples 16.6/16.7 the three variables are not independent of one another.

Table 16.28 Chi-Square Summary Table for Omnibus Analysis of Examples 16.6/16.7

Cell	O_{ijk}	E_{ijk}	$(O_{ijk} - E_{ijk})$	$(O_{ijk} - E_{ijk})^2$	$\frac{(O_{ijk} - E_{ijk})^2}{E_{ijk}}$
111 (N/I,M,H/D)	10	19.30	-9.3	86.49	4.48
121 (N/I,F,H/D)	15	19.30	-4.3	18.49	.96
112(N/I,M,DNH/R)	25	13.20	11.8	139.24	10.55
122(N/I,F,DNH/R)	15	13.20	1.8	3.24	.25
211(NN/E,M,H/D)	25	28.20	-3.2	10.24	.36
221(NN/E,F,H/D)	45	28.20	16.8	282.24	10.01
212(NN/E,M,DNH/R)	20	19.30	.7	.49	.03
222(NN/E,F,DNH/R)	5	19.30	-14.3	204.49	10.60
Sums	160	160	0		$\chi^2 = 37.24$

Test of models of partial independence If the evaluation of the model of **complete independence** through use of the omnibus chi-square analysis yields a significant result, a researcher should conduct additional analyses in order to further clarify the nature of the relationship between the three variables. As noted earlier, among the analyses that can be conducted are those for **partial independence**, which determine whether one variable is independent of the other two variables. Thus, we can determine the following: a) Whether rows are independent of columns and layers; b) Whether columns are independent of rows and layers; and c) Whether layers are independent of rows and columns. The latter three analyses will now be conducted.

Test of independence of rows versus columns and layers Equation 16.26 is employed to determine whether the row variable is independent of the column and layer variables. The only difference in the analysis to be described in this section from the omnibus analysis conducted in the previous section is the computation of the expected frequency for each cell. Equation 16.28 is employed to compute the expected frequency of a cell.

$$E_{ijk} = \frac{(O_{i.})(O_{.j}.O_{..k})}{n} = \frac{(R_i)(C_jL_k)}{n} \quad (\text{Equation 16.28})$$

The notation in Equation 16.28 indicates that to compute the expected frequency of a cell, the number of observations for the row in which that cell appears is multiplied by the number of observations that are in both the column and layer designated for that cell. The resulting product is divided by the total number of observations in the contingency table.

To illustrate, we will compute the expected frequency for the cell in the upper left of [Table 16.27](#). The latter cell, which is Cell₁₁₁ (i.e., the cell in Row 1, Column 1, and Layer 1), represents subjects in the **noise/introvert** category, the **male** category, and the **helped/Democrat** category. We thus multiply the total number of observations in Row 1 (**noise/introvert**) (which is 65) by the total number of observations in both Column 1 and Layer 1 (i.e., observations in the **male** column that are in the **helped/Democrat** layer) (which is 35). The product is divided by the total number of observations in the contingency table (which is 160). Thus: $E_{111} = [(65)(35)]/(160) = 14.22$. The expected frequencies of the remaining seven cells are computed below.

$$E_{121} = [(65)(60)]/(160) = 24.38$$

$$E_{112} = [(65)(45)]/(160) = 18.28$$

$$E_{122} = [(65)(20)]/(160) = 8.13$$

$$E_{211} = [(95)(35)]/(160) = 20.78$$

$$E_{221} = [(95)(60)]/(160) = 35.63$$

$$E_{212} = [(95)(45)]/(160) = 26.72$$

$$E_{222} = [(95)(20)]/(160) = 11.88$$

The chi-square analysis to determine whether the row variable is independent of the column and layer variables is summarized in [Table 16.29](#).

Table 16.29 Chi-Square Summary Table for Rows versus Columns/Layers
Analysis of Examples 16.6/16.7

Cell	O_{ijk}	E_{ijk}	$(O_{ijk} - E_{ijk})$	$(O_{ijk} - E_{ijk})^2$	$\frac{(O_{ijk} - E_{ijk})^2}{E_{ijk}}$
111 (N/I,M,H/D)	10	14.22	-4.22	17.18	1.25
121 (N/I,F,H/D)	15	24.38	-9.38	87.98	3.61
112(N/I,M,DNH/R)	25	18.28	6.72	45.16	2.47
122(N/I,F,DNH/R)	15	8.13	6.87	47.20	5.81
211(NN/E,M,H/D)	25	20.78	4.22	17.81	.86
221(NN/E,F,H/D)	45	35.63	9.37	87.80	2.46
212(NN/E,M,DNH/R)	20	26.72	-6.72	45.16	1.69
222(NN/E,F,DNH/R)	5	11.88	-6.88	47.33	3.98
Sums	160	160	0		$\chi^2 = 22.13$

The degrees of freedom employed in the analysis are $df = rcl - cl - r + 1 = (2)(2)(2) - (2)(2) - 2 + 1 = 3$.³² Employing [Table A4](#), the tabled critical .05 and .01 chi-square values for $df = 3$ are $\chi^2_{.05} = 7.81$ and $\chi^2_{.01} = 11.34$. Since the computed value $\chi^2 = 22.13$ is greater than both of the aforementioned critical values, the null hypothesis can be rejected at both the .05 and .01 levels. By virtue of rejecting the null hypothesis, the researcher can conclude that the row variable (**noise manipulation/introversion-extroversion**) is not independent of the column (**gender**) and layer (**helping/political affiliation**) variables.

Test of independence of columns versus rows and layers Equation 16.26 is employed to determine whether the column variable is independent of the row and layer variables. The only difference in the analysis to be described in this section and the previous analyses described is the computation of the expected frequency for each cell. The data have been reorganized in [Table 16.30](#) to facilitate the computation of the expected frequencies for the analysis of independence of columns versus rows and layers.

Table 16.30 Summary of Data for Examples 16.6/16.7 for Columns versus Rows/Layers Analysis

	Helped/Democrat		Did not help/Republican		Totals
	Noise/Introvert	No Noise/Extrovert	Noise/Introvert	No Noise/Extrovert	
Male	10	25	25	20	80
Female	15	45	15	5	80
Totals	25	70	40	25	160

Equation 16.29 is employed to compute the expected frequency of a cell.

$$E_{ijk} = \frac{(O_{.j.})(O_{i..}O_{..k})}{n} = \frac{(C_j)(R_iL_k)}{n} \quad (\text{Equation 16.29})$$

The notation in Equation 16.29 indicates that to compute the expected frequency of a cell, the number of observations for the column in which that cell appears is multiplied by the number of observations that are in both the row and layer designated for that cell. The resulting product is divided by the total number of observations in the contingency table.

To illustrate, we will compute the expected frequency for the cell in the upper left of [Table 16.30](#). The latter cell, which is Cell₁₁₁ (i.e., the cell in Row 1, Column 1, and Layer 1) represents subjects in the **noise/introvert** category, the **male** category, and the **helped/Democrat** category. We thus multiply the total number of observations in Column 1 (**males**) (which is 80) by the total number of observations in both Row 1 and Layer 1 (i.e., observations in the **noise/introvert** column that are in the **helped/Democrat** layer) (which is 25). The product is divided by the total number of observations in the contingency table (which is 160). Thus: $E_{111} = [(80)(25)]/(160) = 12.5$. The expected frequencies of the remaining seven cells are computed below.

$$E_{121} = [(80)(25)]/(160) = 12.5$$

$$E_{112} = [(80)(40)]/(160) = 20$$

$$E_{122} = [(80)(40)]/(160) = 20$$

$$E_{211} = [(80)(70)]/(160) = 35$$

$$E_{221} = [(80)(70)]/(160) = 35$$

$$E_{212} = [(80)(25)]/(160) = 12.5$$

$$E_{222} = [(80)(25)]/(160) = 12.5$$

The chi-square analysis to determine whether the column variable is independent of the row and layer variables is summarized in [Table 16.31](#).

The degrees of freedom employed in the analysis are $df = rcl - rl - c + 1 = (2)(2)(2) - (2)(2) - 2 + 1 = 3$.³³ Employing [Table A4](#), the tabled critical .05 and .01 chi-square values for $df=3$ are $\chi^2_{.05} = 7.81$ and $\chi^2_{.01} = 11.34$. Since the computed value $\chi^2 = 18.22$ is greater than both of the aforementioned critical values, the null hypothesis can be rejected at both the .05 and .01 levels. By virtue of rejecting the null hypothesis, the researcher can conclude that the column

Table 16.31 Chi-Square Summary Table for Columns versus Rows/Layers
Analysis of Examples 16.6/16.7

Cell	O_{ijk}	E_{ijk}	$(O_{ijk} - E_{ijk})$	$(O_{ijk} - E_{ijk})^2$	$\frac{(O_{ijk} - E_{ijk})^2}{E_{ijk}}$
111 (N/I,M,H/D)	10	12.50	-2.5	6.25	.50
121 (N/I,F,H/D)	15	12.50	2.5	6.25	.50
112(N/I,M,DNH/R)	25	20.00	5.0	25.00	1.25
122(N/I,F,DNH/R)	15	20.00	-5.0	25.00	1.25
211(NN/E,M,H/D)	25	35.00	-10.0	100.00	2.86
221(NN/E,F,H/D)	45	35.00	10.0	100.00	2.86
212(NN/E,M,DNH/R)	20	12.50	7.5	56.25	4.50
222(NN/E,F,DNH/R)	5	12.50	-7.5	56.25	4.50
Sums	160	160	0		$\chi^2 = 18.22$

variable (**gender**) is not independent of the row (**noise manipulation/introversion-extroversion**) and layer (**helping/ political affiliation**) variables.

Test of independence of layers versus rows and columns Equation 16.26 is employed to determine whether the layer variable is independent of the row and column variables. The only difference in the analysis to be described in this section and the previous analyses described is the computation of the expected frequency for each cell. The data have been reorganized in [Table 16.32](#) to facilitate the computation of the expected frequencies for the analysis of independence of layers versus rows and columns.

Table 16.32 Summary of Data for Examples 16.6/16.7 for Layers
versus Rows/Columns Analysis

	Noise/Introvert		No Noise/Extrovert		Totals
	Male	Female	Male	Female	
Helped/Democrat	10	15	25	45	95
Did not Help/Republican	25	15	20	5	65
Totals	35	30	45	50	160

Equation 16.30 is employed to compute the expected frequency of a cell.

$$E_{ijk} = \frac{(O_{..k})(O_{i..} O_{.j.})}{n} = \frac{(L_k)(R_i C_j)}{n} \quad \text{(Equation 16.30)}$$

The notation in Equation 16.30 indicates that to compute the expected frequency of a cell, the number of observations for the layer in which that cell appears is multiplied by the number of observations that are in both the row and column designated for that cell. The resulting product is divided by the total number of observations in the contingency table.

To illustrate, we will compute the expected frequency for the cell in the upper left of [Table 16.32](#). The latter cell, which is Cell₁₁₁ (i.e., the cell in Row 1, Column 1, and Layer 1), represents subjects in the **noise/introvert** category, the **male** category, and the **helped/Democrat** category. We thus multiply the total number of observations in Layer 1 (**helped/Democrat**) (which is 95) by the total number of observations in both Row 1 and Column 1 (i.e., observations in the **noise/introvert** row that are in the **male** column) (which is 35). The product is divided by the total number of observations in the contingency table (which is 160). Thus: $E_{111} = [(95)(35)]/(160) = 20.78$. The expected frequencies of the remaining seven cells are computed below.

$$\begin{aligned}
E_{121} &= [(95)(30)]/(160) = 17.81 \\
E_{112} &= [(65)(35)]/(160) = 14.22 \\
E_{122} &= [(65)(30)]/(160) = 12.19 \\
E_{211} &= [(95)(45)]/(160) = 26.72 \\
E_{221} &= [(95)(50)]/(160) = 29.69 \\
E_{212} &= [(65)(45)]/(160) = 18.28 \\
E_{222} &= [(65)(50)]/(160) = 20.31
\end{aligned}$$

The chi-square analysis to determine whether the layer variable is independent of the row and column variables is summarized in [Table 16.33](#).

Table 16.33 Chi-Square Summary Table for Layers versus Rows/Columns
Analysis of Examples 16.6/16.7

Cell	O_{ijk}	E_{ijk}	$(O_{ijk} - E_{ijk})$	$(O_{ijk} - E_{ijk})^2$	$\frac{(O_{ijk} - E_{ijk})^2}{E_{ijk}}$
111 (N/I,M,H/D)	10	20.78	-10.78	116.21	5.59
121 (N/I,F,H/D)	15	17.81	-2.81	7.90	.44
112(N/I,M,DNH/R)	25	14.22	10.78	116.21	8.17
122(N/I,F,DNH/R)	15	12.19	2.81	7.90	.65
211(NN/E,M,H/D)	25	26.72	-1.72	2.96	.11
221(NN/E,F,H/D)	45	29.69	15.31	234.40	7.89
212(NN/E,M,DNH/R)	20	18.28	1.72	2.96	.16
222(NN/E,F,DNH/R)	5	20.31	-15.31	234.40	11.54
Sums	160	160	0		$\chi^2 = 34.55$

The degrees of freedom employed in the analysis are $df = rcl - rc - l + 1 = (2)(2)(2) - (2)(2) - 2 + 1 = 3$.³⁴ Employing [Table A4](#), the tabled critical .05 and .01 chi-square values for $df = 3$ are $\chi^2_{.05} = 7.81$ and $\chi^2_{.01} = 11.34$. Since the computed value $\chi^2 = 34.55$ is greater than both of the aforementioned critical values, the null hypothesis can be rejected at both the .05 and .01 levels. By virtue of rejecting the null hypothesis, the researcher can conclude that the layer variable (**helping/political affiliation**) is not independent of the row (**noise manipulation/introversion-extroversion**) and column (**gender**) variables.

To clarify the nature of the relationship between the variables with greater precision, it will be necessary to conduct additional analyses on the data. To illustrate this, we will just examine the data in reference to Example 16.6 in greater detail. Recollect that in the latter study there are two independent variables, the **noise manipulation** and **gender**, and a dependent variable, which is the **helping behavior of subjects**. Let us assume that prior to the study the experimenter predicted the following: a) Subjects exposed to the **no noise** condition will be more likely to **help the confederate** than subjects exposed to the **noise condition**; and b) Subjects exposed to a **female** confederate will be more likely to **help** than subjects exposed to a **male** confederate. The two aforementioned hypotheses are predicting what is referred to as a **main effect** on both of the independent variables. The term **main effect** (which is discussed in greater detail in Sections I and V of the **between-subjects factorial analysis of variance**) describes the effect of one independent variable (also referred to as a factor) on the dependent variable, ignoring any effect any of the other independent variables/factors might have on the dependent variable. If the researcher considers each independent variable separately, two 2×2 contingency tables can be constructed to summarize the data. The latter is done with [Tables 16.34](#) and [16.35](#), which, respectively,

Table 16.34 Summary of Data for Example 16.6 Employing Only Noise Manipulation Independent Variable

	Helped the Confederate	Did not Help the Confederate	Totals
Noise	25	40	65
No Noise	70	25	95
Totals	95	65	160

Table 16.35 Summary of Data for Example 16.6 Employing Only Gender Independent Variable

	Helped the Confederate	Did not Help the Confederate	Totals
Male	35	45	80
Female	60	20	80
Totals	95	65	160

summarize the data when the **noise manipulation** independent variable is considered by itself and when the **gender** independent variable is considered by itself.

With regard to the predicted main effects, consider the following information that can be derived from [Tables 16.34](#) and [16.35](#).

Without employing a test of significance on the data (which in this case would be the **chi-square test for homogeneity/z test for two independent proportions**), it appears that a subject is more likely to **help** in the **no noise** condition than the **noise** condition. This is the case, since the proportion of subjects who **helped** the confederate in the **no noise** condition is $70/95 = .74$, while the proportion of subjects who helped the confederate in the **noise** condition is only $25/65 = .38$. This clearly suggests the presence of a **main effect** on the **noise manipulation** independent variable. In other words, if in analyzing the data the researcher does not bother to consider **gender** as a second independent variable, but considers the **noise manipulation** as the only independent variable, the researcher will conclude that subjects are more likely to **help the confederate** in the **no noise** condition rather than in the **noise** condition.

Without employing a test of significance on the data (which in this case would be the **chi-square test for homogeneity/z test for two independent proportions**), it appears that a subject is more likely to **help** a **female** confederate than a **male** confederate. This is the case, since the proportion of subjects who **helped** the **female** confederate is $60/80 = .75$, while the proportion of subjects who helped the **male** confederate is only $35/80 = .44$. This clearly suggests the presence of a **main effect** on the **gender** independent variable. In other words, if in analyzing the data the researcher does not bother to consider the **noise manipulation** as a second independent variable, but considers **gender** as the only independent variable, the researcher will conclude that subjects are more likely to **help the female confederate** rather than the **male confederate**.

It was noted earlier in the discussion of **Simpson's paradox** that when data based on three variables are collapsed into two 2×2 contingency tables, a distorted picture of what actually occurred in a study may result. In the case of Example 16.6, there appears to be a definite interaction between the **independent variables** of **noise** and **gender**. Although for Example 16.6 the conclusions that will be reached if one employs two 2×2 contingency tables (i.e., [Tables 16.34](#) and [16.35](#)) are not as skewed as in the example employed to demonstrate **Simpson's paradox**, the use of two 2×2 tables still does not present an entirely accurate picture of what occurred in the study. To be more specific, the 2×2 tables are unable to reveal the interaction between the two independent variables. Specifically, consider the following, all of which are summarized in

Table 16.36: a) The proportion of subjects who **helped** who were exposed to **noise** and a **male** confederate is $10/35 = .29$; b) The proportion of subjects who **helped** who were exposed to **noise** and a **female** confederate is $15/30 = .50$; c) The proportion of subjects who **helped** who were exposed to **no noise** and a **male** confederate is $25/45 = .56$; and d) The proportion of subjects who **helped** who were exposed to **no noise** and a **female** confederate is $45/50 = .90$. Note that in **Table 16.36**, the proportion .44 for **males** in Column 1 is the proportion of all subjects exposed to a **male** confederate who helped ($35/80 = .44$). The proportion .75 for **females** in Column 2 is the proportion of all subjects exposed to a **female** confederate who helped ($60/80 = .75$). The proportion .38 for **noise** in Row 1 is the proportion of all subjects exposed to **noise** who helped ($25/65 = .38$). The proportion .74 for **no noise** in Row 2 is the proportion of all subjects exposed to **no noise** who helped ($70/95 = .74$).

**Table 16.36 Summary of Interaction for Example 16.6:
Proportions of Helping Across Both Independent Variables**

	Male	Female	Row proportions
Noise	.29	.50	.38
No Noise	.56	.90	.74
Column proportions	.44	.74	

As noted earlier, an interaction is present in a set of data when the performance of subjects on one independent variable is not consistent across all the levels of another independent variable. Examination of **Table 16.36** clearly suggests the presence of an interaction. Specifically, the following appears to be the case: Subjects are more likely to help a **female** confederate than a **male** confederate, but the proportion of **females** helped relative to the proportion of **males** helped is larger in the **no noise** condition than in the **noise** condition. We can also say that subjects are more likely to help the confederate in the **no noise** condition than the **noise** condition, but the proportion of subjects who help in the **no noise** condition relative to the **noise** condition is larger when the confederate is a **female** as opposed to a **male**.

Tables such as **Table 16.36**, as well as graphs (such as **Figures 27.1** and **27.2** employed to illustrate an interaction for a **between-subjects factorial analysis of variance**), can be extremely useful in providing a researcher with visual information regarding whether or not an interaction is present in a set of data.³⁵ It should be emphasized that in order to definitively establish the presence of an interaction, it is required that the appropriate inferential statistical statistic be conducted, and that the latter test yields a significant result for the interaction in question.

As noted earlier, the analysis of multidimensional contingency tables is a complex subject, and the discussion of it in this section has been limited in nature. Among those sources that discuss the subject in greater detail are Christensen (1990), Everitt (1977, 1992), Fienberg (1980), Marascuilo and McSweeney (1977), Marascuilo and Serlin (1988), Wickens (1989), and Zar (1999).

VIII. Additional Examples Illustrating the Chi-Square Test for $r \times c$ Tables

Examples 16.8–16.11 are additional examples that can be evaluated with the **chi-square test for $r \times c$ tables**.

Example 16.8 *A researcher conducts a study to evaluate the relative problem-solving ability of male versus female adolescents. One hundred males and 80 females are randomly selected*

from a population of adolescents. Each subject is given a mechanical puzzle to solve. The dependent variable is whether or not a person is able to solve the puzzle. Sixty out of the 100 male subjects are able to solve the puzzle, while only 30 out of the 80 female subjects are able to solve the puzzle. Is there a significant difference between males and females with respect their ability to solve the puzzle?

Table 16.37 summarizes the data for Example 16.8. Example 16.8 conforms to the requirements of the **chi-square test for homogeneity**. This is the case, since there are two independent samples/groups (**males** versus **females**) which are dichotomized with respect to the following two categories on the dimension of problem-solving ability: **solved puzzle** versus **did not solve puzzle**. The grouping of subjects on the basis of gender represents a nonmanipulated independent variable, while the problem-solving performance of subjects represents the dependent variable. Note that the number of people for each gender is predetermined by the experimenter. Also note that it is not necessary to have an equal number of observations in the categories of the row variable, which represents the independent variable. Since the independent variable is nonmanipulated, if the chi-square analysis is significant it will only allow the researcher to conclude that a significant association exists between gender and one's ability to solve the puzzle. The researcher cannot conclude that gender is the direct cause of any observed differences in problem-solving ability between males and females. Employing Equation 16.2, the obtained chi-square value for Table 16.37 is $\chi^2 = 9$, which for $df = 1$ is greater than $\chi^2_{.05} = 3.84$ and $\chi^2_{.01} = 6.63$. Thus, the null hypothesis can be rejected at both the .05 and .01 levels. Inspection of Table 16.37 reveals that a larger proportion of **males** are able to solve the puzzle than **females**.

Table 16.37 Summary of Data for Example 16.8

	Solved puzzle	Did not solve puzzle	Row sums
Males	60	40	100
Females	30	50	80
Column sums	90	90	Total observations 180

Example 16.9 A pollster conducts a survey to evaluate whether Caucasians and African-Americans differ in their attitude toward gun control. Five hundred people are randomly selected from a telephone directory and called at 8 P.M. in the evening. An interview is conducted with each individual, at which time a person is categorized with respect to both race and whether one supports or opposes gun control. Table 16.38 summarizes the results of the survey. Is there evidence of racial differences with respect to attitude toward gun control?

This example conforms to the requirements of the **chi-square test of independence**, since a single sample is categorized on two dimensions. The two dimensions subjects are categorized with respect to are race, for which there are the two categories **Caucasian** versus **African-American**, and attitude toward gun control, for which there are the two categories **supports gun control** versus **opposes gun control**. Note that neither the number of **Caucasians** or **African-Americans** (i.e., the sums of the rows), or the people who **support gun control** or **oppose gun control** (i.e., the sums of the columns) are predetermined prior to the pollster conducting the survey. The pollster selects a single sample of 500 subjects and categorizes them on both dimensions after the data are collected. The obtained chi-square value for Table 16.38 is $\chi^2 = 59.91$, which for $df = 1$ is greater than $\chi^2_{.05} = 3.84$ and $\chi^2_{.01} = 6.63$. Thus, the null hypothesis can be rejected at both the .05 and .01 levels. Inspection of Table 16.38 reveals that

a larger proportion of **Caucasians opposes gun control**, whereas a larger proportion of **African-Americans supports gun control**.

Table 16.38 Summary of Data for Example 16.9

	Supports gun control	Opposes gun control	Row sums
Caucasians	120	170	290
Afro-Americans	160	50	210
Column sums	280	220	Total observations 500

Example 16.10 A researcher conducts a study on a college campus to examine the relationship between a student's class standing and the number of times a student visits a physician during the school year. **Table 16.39** summarizes the responses of a random sample of 280 students employed in the study. Do the data indicate that the number of visits a student makes to a physician is independent of his or her class standing?

Table 16.39 Summary of Data for Example 16.10

	0 visits	1–5 visits	More than 5 visits	Row sums
Freshman	20	6	24	60
Sophomore	30	10	10	50
Junior	50	30	10	90
Senior	19	11	50	80
Column sums	119	67	94	Total observations 280

This example conforms to the requirements of the **chi-square test of independence**, since a single sample is categorized on two dimensions. The two dimensions subjects are categorized with respect to are class standing, for which there are the four categories: **Freshman, Sophomore, Junior, Senior**, and the number of visits to a physician, for which there are the three categories: **0 visits, 1–5 visits, more than 5 visits**. Note that neither the sums of the rows nor the columns is predetermined by the researcher. The researcher randomly selects 280 subjects and categorizes each subject on both dimensions after the data are collected. Since the data for Example 16.10 are identical to that employed in Example 16.5, it yields the same result. The null hypothesis can be rejected, since the obtained value $\chi^2 = 59.16$ is significant at both the .05 and .01 levels. Thus, the researcher can conclude that a student's class standing and the number of visits one makes to a physician are not independent of one another (i.e., the two dimensions seem to be associated/ correlated with one another). As is the case with Example 16.5, a more detailed analysis of the data can be conducted through use of the comparison procedures described in Section VI.

Example 16.11 A researcher conducts a study to evaluate whether or not a nationally acclaimed astrologer is able to match subjects with their correct sun sign. The astrologer and researcher agree to employ a format in which the astrologer views a five minute videotape of a subject who verbally responds to five open ended questions of a personal nature. Upon viewing the videotape, the astrologer indicates which of the 12 sun signs he believes the person's birth data falls within. Over a three-month period the astrologer views videotapes for 718 subjects.

Table 16.40 summarizes the results of the study. Since each column of the table corresponds to a subject's actual sun sign, and each row the sun sign selected by the astrologer, all correct responses by the astrologer appear in the 12 cells that constitute the diagonal of the table (i.e., any cell in which the row and column labels are identical). Does the performance of the astrologer indicate that he can reliably identify a person's sun sign?

Table 16.40 Astrology Study Data

Selected sun sign	Actual Sun Sign												Column sums
	Aquarius	Pisces	Aries	Taurus	Gemini	Cancer	Leo	Virgo	Libra	Scorpio	Sagit- tarius	Capri- corn	
Aquarius	6	2	4	8	5	3	9	7	2	8	6	4	64
Pisces	3	2	0	5	7	1	9	9	4	2	8	7	57
Aries	0	9	3	1	7	6	2	1	9	8	9	4	59
Taurus	9	3	4	3	4	8	1	8	5	6	2	6	59
Gemini	8	8	2	6	3	9	4	6	4	1	3	9	63
Cancer	6	6	4	7	7	7	2	4	6	3	8	1	61
Leo	7	7	1	4	9	9	3	9	2	1	4	6	62
Virgo	2	4	6	8	8	7	1	0	3	5	1	9	54
Libra	8	8	8	8	3	6	2	9	0	6	2	4	64
Scorpio	5	1	9	0	0	5	7	9	9	0	6	6	57
Sagittarius	0	4	7	7	8	3	6	1	9	2	9	0	56
Capricorn	7	0	5	9	5	2	0	7	9	8	6	4	62
Row sums	61	54	53	66	66	66	46	70	62	50	64	60	718

Table 16.40 summarizes the results of the study in the format of a 12×12 contingency table. Since the table is based on a single sample of subjects who are categorized two times (i.e., each subject is categorized by the astrologer with regard to sun sign and categorized on the basis of one's actual birth date), the **chi-square test of independence** can be employed to evaluate the body of data contained within the whole table. However, the latter analysis will really not address the question of primary interest with any degree of precision. The simplest and most straightforward analysis will be to determine whether the number of correct responses by the astrologer is significantly above chance expectation. Thus, instead of evaluating the data with the **chi-square test of independence**, we will employ the **binomial sign test for a single-sample**, which will be used to evaluate the number of correct responses in the diagonal of the table.

Equation 9.7 will be employed to evaluate the data.³⁶ If the astrologer is just guessing a person's sun sign, he has a one in 12 chance of being correct, and an 11 in 12 chance of being incorrect.³⁷ Thus, the expected number of correct responses will be the total number of responses (which corresponds to the total number of subjects/observations) multiplied by $1/12$. Employing Equation 9.1, the expected number of correct responses is computed to be $\mu = n\pi_1 = (718)(1/12) = 59.83$. Equation 9.2 is employed to compute the standard deviation of the binomially distributed variable: $\sigma = \sqrt{n\pi_1\pi_2} = \sqrt{(718)(1/12)(11/12)} = 7.41$. Since the sum of the 12 values in the diagonal of the Table 16.40 equals 40, the value $x = 40$ is employed to represent the number of correct responses in Equation 9.7. Substituting the appropriate values in the latter equation, the value $z = -2.68$ is computed. The negative z value is consistent with the fact that the number of correct responses is below chance expectation. Certainly the latter, in and of itself, invalidates the astrologer's claim that he can reliably identify a person's sun sign.

$$z = \frac{x - n\pi_1}{\sqrt{n\pi_1\pi_2}} = \frac{40 - (718)(1/12)}{\sqrt{(718)(1/12)(11/12)}} = \frac{40 - 59.83}{7.41} = -2.68$$

The obtained value $z = -2.68$ is evaluated with **Table A1** in the **Appendix**. In **Table A1** the tabled critical two-tailed .05 and .01 values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed .05 and .01 values are $z_{.05} = 1.65$ and $z_{.01} = 2.33$. Since the absolute value $z = 2.68$ is larger than all of the aforementioned critical values, both the nondirectional alternative hypothesis and the directional alternative hypothesis that is consistent with the data are supported. Put simply, the researcher will conclude that the astrologer's performance is significantly below chance.

Given the fact that **Table 16.40** is a 12×12 contingency table, there are numerous other analyses that can be conducted on the data. For instance, the researcher can examine the accuracy of the astrologer's responses within each of the sun signs. As an example, with respect to the sun sign Sagittarius, the astrologer correctly identified 9 of the 64 subjects who are, in fact, a Sagittarius. Since the chance probability of a correct response within a given sun sign is also $1/12$, it turns out that a score of 9 is significantly above chance (if a one-tailed analysis is conducted). On the other hand, the astrologer's scores of 0 for Virgo, Libra, and Scorpio are all significantly below chance. The point to be made here is that if one sifts through a large body of data, just by chance some results will be significant, and some of the significant results will be in the direction toward which a researcher is biased. Thus, if there is reason to believe that a specific element of the data will be significant, it should be specified beforehand. If the latter then turns out to be significant, that is quite different from finding the same significant difference after the fact.

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Endnotes

1. A general discussion of the chi-square distribution can be found under the **single-sample chi-square test for a population variance**.
2. The use of the chi-square approximation (which employs a continuous probability distribution to approximate a discrete probability distribution) is based on the fact that the computation of exact probabilities requires an excessive amount of calculations.
3. In the case of both the **chi-square test of independence** and the **chi-square test of homogeneity**, the same result will be obtained regardless of which of the variables is designated as the row variable versus the column variable.
4. It is just coincidental that the number of **introverts** equals the number of **extroverts**.
5. In the context of the discussion of the **chi-square test of independence**, the proportion of observations in Cell₁₁ refers to the number of observations in Cell₁₁ divided by the total number of observations in the 2 × 2 table. In the discussion of the hypothesis for the **chi-square test for homogeneity**, the proportion of observations in Cell₁₁ refers to the number of observations in Cell₁₁ divided by the total number of observations in Row 1 (i.e., the row in which Cell₁₁ appears).
6. Equation 16.2 is an extension of Equation 8.2 (which is employed to compute the value of chi-square for the **chi-square goodness-of-fit test**) to a two-dimensional table. In Equation 16.2, the use of the two summation expressions $\sum_{i=1}^r \sum_{j=1}^c$ indicates that the operations summarized in Table 16.4 are applied to all of the cells in the $r \times c$ table. In contrast, the single summation expression $\sum_{i=1}^k$ in Equation 8.2 indicates that the operations summarized in Table 8.2 are applied to all k cells in a one-dimensional table.
7. The same chi-square value will be obtained if the row and column variables are reversed — i.e., the helping variable represents the row variable and the noise variable represents the column variable.
8. Correlational studies are discussed in detail under the **Pearson product-moment correlation coefficient**.
9. The value $\chi^2_{.98} = 5.43$ is determined by interpolation. It can also be derived by squaring the tabled critical one-tailed .01 value $z_{.01} = 2.33$, since the square of the latter value is equivalent to the chi-square value at the 98th percentile. The use of z values in reference to a 2 × 2 contingency table is discussed later in this section under the **z test for two independent proportions**.

10. Within the framework of this discussion, the value $\chi^2_{.05} = 3.84$ represents the tabled chi-square value at the 95th percentile (which demarcates the extreme 5% in the right tail of the chi-square distribution). Thus, using the format employed for the one-tailed .05 and .01 values, the notation identifying the two-tailed .05 value can be written as $\chi^2_{.95} = 3.84$. In the same respect, the value $\chi^2_{.01} = 6.63$ represents the tabled chi-square value at the 99th percentile (which demarcates the extreme 1% in the right tail of the chi-square distribution). Thus, using the format employed for the one-tailed .05 and .01 values, the notation identifying the two-tailed .01 value can be written as $\chi^2_{.99} = 6.63$.
11. The null and alternative hypotheses presented for the **Fisher exact test** in this section are equivalent to the alternative form for stating the null and alternative hypotheses for the **chi-square test of homogeneity** presented in Section III (if the hypotheses in Section III are applied to a 2×2 contingency table).
12. Sourcebooks documenting statistical tables (e.g., Owen (1962) and Beyer (1968)), as well as many books that specialize in nonparametric statistics (e.g., Daniel (1990); Marascuilo and McSweeney (1977); Siegel and Castellan (1988)) contain tables of the hypergeometric distribution that can be employed with 2×2 contingency tables. Such tables eliminate the requirement of employing Equations 16.7/16.8 to compute the value of P_T .
13. The value $(1 - p)$, which is often represented by the notation q , can also be computed as follows: $q = (1 - p) = (b + d) / (n_1 + n_2) = (b + d) / n$. The value q is a pooled estimate of the proportion of observations in Column 2 in the underlying population.
14. Due to rounding off error there may be a minimal discrepancy between the square of a z value and the corresponding chi-square value.
15. The logic for employing Equation 16.11 in lieu of Equation 16.9 is the same as that discussed in reference to the ***t* test for two independent samples**, when in the case of the latter test the null hypothesis stipulates a value other than zero for the difference between the population means (and Equation 11.5 is employed to compute the test statistic in lieu of Equations 11.1/11.2/11.3).
16. The denominator of Equation 16.11 is employed to compute $s_{p_1 - p_2}$ instead of the denominator of Equation 16.9, since in computing a confidence interval it cannot be assumed that $\pi_1 = \pi_2$ (which is assumed in Equation 16.9, and serves as the basis for computing a pooled p value in the latter equation).
17. The **median test for independent samples** can also be employed within the framework of the model for the **chi-square test of independence**. To illustrate this, assume that Example 16.4 is modified so that the researcher randomly selects a sample of 200 subjects, and does not specify beforehand that the sample is comprised of 100 females and 100 males. If it just happens by chance that the sample is comprised of 100 females and 100 males, one can state that neither the sum of the rows nor the sum of the columns is predetermined by the researcher. As noted in Section I, when neither of the marginal sums is predetermined, the design conforms to the model for the **chi-square test of independence**.
18. The word **column** can be interchanged with the word **row** in the definition of a complex comparison.

19. Another consideration that should be mentioned with respect to conducting comparisons is that two or more comparisons for a set of data can be **orthogonal** (which means they are independent of one another), or comparisons can overlap with respect to the information they provide. As a general rule, when a limited number of comparisons is planned, it is most efficient to conduct orthogonal comparisons. The general subject of orthogonal comparisons is discussed in greater detail in Section VI of the **single-factor between-subjects analysis of variance**.
20. The null and alternative hypotheses stated below do not apply to the **odds ratio**.
21. Some sources note that the **phi coefficient** can only assume a range of values between 0 and +1. In these sources, the term $|ad - bc|$ is employed in the numerator of Equation 16.17. By employing the absolute value of the term in the numerator of Equation 16.17, the value of **phi** will always be a positive number. Under the latter condition the following will be true: $\phi = \sqrt{\chi^2/n}$.
22. In the case of small sample sizes, the results of the **Fisher exact test** are employed as the criterion for determining whether the computed value of **phi** is significant.
23. In such a case, the data are summarized in the form of a 2×2 contingency table documenting the proportion of subjects who answer in each of the categories of two dichotomous variables (e.g., **True** versus **False** for both variables/test items).
24. The reason why the result of the **chi-square test for $r \times c$ tables** is not employed to assess the significance of Q is because Q is not a function of chi-square. It should be noted that since Q is a special case of **Goodman and Kruskal's gamma**, it can be argued that Equation 32.2 (the significance test for **gamma**) can be employed to assess whether or not Q is significant. However, Ott *et al.* (1992) state that a different procedure is employed for evaluating the significance of Q versus **gamma**. Equation 32.2 will not yield the same result as that obtained with Equation 16.21 when it is applied to a 2×2 table. If the **gamma** statistic is computed for Examples 16.1/16.2 it yields the absolute value $\gamma = .56$ (γ is the lower case Greek letter **gamma**), which is identical to the value of Q computed for the same set of data. (The absolute value is employed since the contingency table is not ordered, and thus, depending upon how the cells are arranged, a value of either +.56 or -.56 can be derived for **gamma**.) However, when Equation 32.2 is employed to assess the significance of $\gamma = .56$, it yields the absolute value $z = 3.51$, which although significant at both the .05 and .01 levels is lower than the absolute value $z = 5.46$ obtained with Equation 16.21.
25. An excellent discussion of odds can be found in Christensen (1990).
26. a) One can also divide .439 by 1.5 and obtain the value $o = .29$. The latter value indicates that the odds of **helping** in the **noise** condition are .29 times as large as the odds of **helping** in the **no noise** condition. In the case of the data in [Table 16.23](#), the value $o = .29$ indicates that the odds of **contracting the disease** in the **washes hands** condition are .29 times as large as the odds of **contracting the disease** in the **does not wash** condition; b) As noted earlier, when odds are employed what is often stated are the odds that an event will not occur. Using this definition, the odds that a person in the **noise** condition **did not help the confederate** (or that someone who **washes her hands** does **not contract the disease**) are 2.33:1 (since $(70/100)/(30/100) = 2.33$). The odds that a person in the **no noise** condition

did not help the confederate (or that someone who **does not wash her hands** does **not contract the disease**) are .667:1 or 2:3 (since $(40/100)/(60/100) = .667$). These values yield the same **odds ratio**, since $2.33/.667 = 3.49$.

27. Equation 16.31 is an alternate equation for computing the **odds ratio**.

$$o = \frac{p_b p_c}{p_a p_d} \quad \text{(Equation 16.31)}$$

From [Tables 16.2/16.23](#), we can determine that $p_a = a/n = 30/200 = .15$, $p_b = b/n = 70/200 = .35$, $p_c = c/n = 60/200 = .3$, and $p_d = d/n = 40/200 = .2$. Employing Equation 16.31 with the data for Example 16.1, the value $o = 3.5$ is computed.

$$o = \frac{(.35)(.3)}{(.15)(.2)} = 3.5$$

28. Pagano and Gauvreau (1993) note that if the expected frequencies for any of the cells in the contingency table are less than 5, the equation below should be employed to compute the standard error.

$$SE = \sqrt{\frac{1}{a + .5} + \frac{1}{b + .5} + \frac{1}{c + .5} + \frac{1}{d + .5}}$$

29. **Yates' correction for continuity** was not used to compute the values $\chi^2 = 11.58$ and $\chi^2 = 2.09$ for the two hospitals. If **Yates' correction** is used, the computed chi-square values will be a little lower.
30. Some sources (e.g., Christensen (1990)) employ the term **factors** (which is the term that is commonly employed within the framework of a **factorial analysis of variance**) to identify the different independent variables.
31. Zar (1999) notes that the degrees of freedom are the sum of the degrees of freedom for all of the interactions. Specifically $df = rcl - r - c - l + 2 = (r - 1)(c - 1)(l - 1) + (r - 1)(c - 1) + (r - 1)(l - 1) + (c - 1)(l - 1)$.
32. Zar (1999) notes that the degrees of freedom are the sum of the following: $df = rcl - cl - r + 1 = (r - 1)(c - 1)(l - 1) + (r - 1)(c - 1) + (r - 1)(l - 1)$.
33. Based on Endnote 32, it logically follows that the degrees of freedom are the sum of the following: $df = rcl - rl - c + 1 = (r - 1)(c - 1)(l - 1) + (c - 1)(r - 1) + (c - 1)(l - 1)$.
34. Based on Endnote 32, it logically follows that the degrees of freedom are the sum of the following: $df = rcl - rc - l + 1 = (r - 1)(c - 1)(l - 1) + (l - 1)(r - 1) + (l - 1)(c - 1)$.
35. Zar (1999) discusses and cites reference on **mosaic displays** for contingency tables, which represent an alternative to conventional graphs for visually summarizing the data in a contingency table.
36. Since Equations 9.6 and 9.7 are equivalent, either one can be employed for the analysis. In

addition, since our analysis involves a binary situation (i.e., the two response categories of **being correct** or **incorrect**), the data can also be evaluated with the **chi-square goodness-of-fit test**. The chi-square value obtained with the latter test will be equal to the square of the z value obtained with Equation 9.6/9.7.

37. In actuality, the number of days in each sun sign is not one-twelfth of the total number of days in a year (since 365 cannot be divided evenly by 12, it logically follows that the number of days in each sun sign will not be equal). In spite of the latter, for all practical purposes the value $1/12$ can be accurately employed to represent the probability for each sun sign.

Inferential Statistical Tests Employed with Two Dependent Samples (and Related Measures of Association/Correlation)

Test 17: [The \$t\$ Test for Two Dependent Samples](#)

Test 18: [The Wilcoxon Matched-Pairs Signed-Ranks Test](#)

Test 19: [The Binomial Sign Test for Two Dependent Samples](#)

Test 20: [The McNemar Test](#)

Test 17

The t Test for Two Dependent Samples (Parametric Test Employed with Interval/Ratio Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test Do two dependent samples represent two populations with different mean values?

Relevant background information on test The t test for two dependent samples, which is employed in a hypothesis testing situation involving two dependent samples, is one of a number of inferential statistical tests that are based on the t distribution (which is described in detail under the **single-sample t test (Test 2)**). Throughout the discussion of the t test for two dependent samples, the term **experimental conditions** will also be employed to represent the **dependent samples** employed in a study. In a **dependent samples design**, each subject either serves in all of the k (where $k \geq 2$) experimental conditions, or else is matched with a subject in each of the other $(k - 1)$ experimental conditions (matching is discussed in Section VII).¹ In designs that are evaluated with the t test for two dependent samples, the value of k will always equal 2.

In conducting the t test for two dependent samples, the means of the two experimental conditions (represented by the notations \bar{X}_1 and \bar{X}_2) are employed to estimate the values of the means of the populations (μ_1 and μ_2) the conditions represent. If the result of the t test for two dependent samples is significant, it indicates the researcher can conclude there is a high likelihood that the two experimental conditions represent populations with different mean values. It should be noted that the t test for two dependent samples is the appropriate test to employ for contrasting the means of two dependent samples when the values of the underlying population variances are unknown. In instances where the latter two values are known, the appropriate test to employ is the z test for two dependent samples (Test 17e), which is described in Section VI.

The t test for two dependent samples is employed with interval/ratio data, and is based on the following assumptions: a) The sample of n subjects has been randomly selected from the population it represents; b) The distribution of data in the underlying populations each of the experimental conditions represents is normal; and c) The third assumption, which is referred to as the **homogeneity of variance** assumption, states that the variance of the underlying population represented by Condition 1 is equal to the variance of the underlying population represented by Condition 2 (i.e., $\sigma_1^2 = \sigma_2^2$). It should be noted that the t test for two dependent samples is more sensitive to violation of the homogeneity of variance assumption (which is discussed in Section VI) than is the t test for two independent samples (Test 11). If any of the aforementioned assumptions of the t test for two dependent samples are saliently violated, the reliability of the test statistic may be compromised.

When a study employs a dependent samples design, the following two issues related to experimental control must be taken into account: a) In a dependent samples design in which each subject serves in both experimental conditions, it is essential that the experimenter controls for

order effects (also known as **sequencing** or **carryover effects**). An **order effect** is where an obtained difference on the dependent variable is a direct result of the order of presentation of the experimental conditions, rather than being due to the independent variable manipulated by the experimenter. Order effects can be controlled through the use of a technique called **counterbalancing**, which is discussed in Section VII; and b) When a dependent samples design employs matched subjects, within each pair of matched subjects each of the two subjects must be randomly assigned to one of the two experimental conditions. Nonrandom assignment of subjects to the experimental conditions can compromise the **internal validity** of a study.² A more thorough discussion of **matching** can be found in Section VII.

II. Example

Example 17.1 *A psychologist conducts a study to determine whether or not people exhibit more emotionality when they are exposed to sexually explicit words than when they are exposed to neutral words. Each of ten subjects is shown a list of 16 randomly arranged words, which are projected onto a screen one at a time for a period of five seconds. Eight of the words on the list are sexually explicit and eight of the words are neutral. As each word is projected on the screen, a subject is instructed to say the word softly to him or herself. As a subject does this, sensors attached to the palms of the subject's hands record galvanic skin response (GSR), which is used by the psychologist as a measure of emotionality. The psychologist computes two scores for each subject, one score for each of the experimental conditions: **Condition 1: GSR/Explicit** — The average GSR score for the eight sexually explicit words; **Condition 2: GSR/Neutral** — The average GSR score for the eight neutral words. The GSR/Explicit and the GSR/Neutral scores of the ten subjects follow. (The higher the score, the higher the level of emotionality.) **Subject 1** (9, 8); **Subject 2** (2, 2); **Subject 3** (1, 3); **Subject 4** (4, 2); **Subject 5** (6, 3); **Subject 6** (4, 0); **Subject 7** (7, 4); **Subject 8** (8, 5); **Subject 9** (5, 4); **Subject 10** (1, 0).³ Do subjects exhibit differences in emotionality with respect to the two categories of words?*

III. Null versus Alternative Hypotheses

Null hypothesis $H_0: \mu_1 = \mu_2$

(The mean of the population Condition 1 represents equals the mean of the population Condition 2 represents.)

Alternative hypothesis $H_1: \mu_1 \neq \mu_2$

(The mean of the population Condition 1 represents does not equal the mean of the population Condition 2 represents. This is a **nondirectional alternative hypothesis** and it is evaluated with a **two-tailed test**. In order to be supported, the absolute value of t must be equal to or greater than the tabled critical two-tailed t value at the prespecified level of significance. Thus, either a significant positive t value or a significant negative t value will provide support for this alternative hypothesis.)

or

$H_1: \mu_1 > \mu_2$

(The mean of the population Condition 1 represents is greater than the mean of the population Condition 2 represents. This is a **directional alternative hypothesis** and it is evaluated with a **one-tailed test**. It will only be supported if the sign of t is positive, and the absolute value of t

is equal to or greater than the tabled critical one-tailed t value at the prespecified level of significance.)

or

$$H_1\colon \mu_1 < \mu_2$$

(The mean of the population Condition 1 represents is less than the mean of the population Condition 2 represents. This is a **directional alternative hypothesis** and it is evaluated with a **one-tailed test**. It will only be supported if the sign of t is negative, and the absolute value of t is equal to or greater than the tabled critical one-tailed t value at the prespecified level of significance.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis (H_0) is rejected.⁴

IV. Test Computations

Two methods can be employed to compute the test statistic for the **t test for two dependent samples**. The method to be described in this section, which is referred to as the **direct-difference method**, allows for the quickest computation of the t statistic. In Section VI, a computationally equivalent but more tedious method for computing t is described.

Table 17.1 Data for Example 17.1

Subject	Condition 1	Condition 2	D	D^2
	X_1	X_2		
1	9	8	1	1
2	2	2	0	0
3	1	3	-2	4
4	4	2	2	4
5	6	3	3	9
6	4	0	4	16
7	7	4	3	9
8	8	5	3	9
9	5	4	1	1
10	1	0	1	1
$\Sigma X_1 = 47$		$\Sigma X_2 = 31$	$\Sigma D = -2$ $\Sigma D+ = 18$	$\Sigma D^2 = 54$
			$\Sigma D = 16$	
$\bar{X}_1 = \frac{47}{10} = 4.7$		$\bar{X}_2 = \frac{31}{10} = 3.1$		

The data for Example 17.1 and the preliminary computations for the **direct-difference method** are summarized in Table 17.1. Note that there are $n = 10$ subjects, and that there is a total of $2n = (2)(10) = 20$ scores, since each subject has two scores. The two scores of the 10 subjects are listed in the columns of Table 17.1 labelled X_1 and X_2 . The score of a subject in the column labelled X_1 is the average GSR score of the subject for the eight sexually explicit words (Condition 1), while the score of a subject in the column labelled X_2 is the average GSR score of the subject for the eight neutral words (Condition 2). Column 4 of Table 17.1 lists a difference score for each subject (designated by the notation D), which is computed by subtracting a

subject's X_2 score from his X_1 score (i.e., $D = X_1 - X_2$). Column 5 of the table lists a D^2 score for each subject, which is obtained by squaring a subject's D score.

In Column 4 of [Table 17.1](#), the summary value $\Sigma D = 16$ is obtained by adding $\Sigma D+ = 18$, the sum of the positive difference scores (i.e., all those difference scores with a + sign), and $\Sigma D- = -2$, the sum of the negative difference scores (i.e., all those difference scores with a - sign). The reader should take note of the fact that whenever $\Sigma X_1 > \Sigma X_2$ (and consequently $\bar{X}_1 > \bar{X}_2$), the value ΣD will be a positive number, whereas whenever $\Sigma X_1 < \Sigma X_2$ (and consequently $\bar{X}_1 < \bar{X}_2$), the value ΣD will be a negative number.

Equation 17.1 is the direct-difference equation for computing the test statistic for the ***t* test for two dependent samples**.

$$t = \frac{\bar{D}}{s_{\bar{D}}} \quad (\text{Equation 17.1})$$

Where: \bar{D} represents the mean of the difference scores
 $s_{\bar{D}}$ represents the **standard error of the mean difference**

The **mean of the difference scores** is computed with Equation 17.2.

$$\bar{D} = \frac{\Sigma D}{n} \quad (\text{Equation 17.2})$$

Employing Equation 17.2, the value $\bar{D} = 1.6$ is computed.

$$\bar{D} = \frac{16}{10} = 1.6$$

Equation 17.3 is employed to compute \tilde{s}_D , which represents the estimated population standard deviation of the difference scores.⁵

$$\tilde{s}_D = \sqrt{\frac{\Sigma D^2 - \frac{(\Sigma D)^2}{n}}{n - 1}} \quad (\text{Equation 17.3})$$

Employing Equation 17.3, the value $\tilde{s}_D = 1.78$ is computed.

$$\tilde{s}_D = \sqrt{\frac{54 - \frac{(16)^2}{10}}{10 - 1}} = 1.78$$

Equation 17.4 is employed to compute the value $s_{\bar{D}}$. The value $s_{\bar{D}}$ represents the **standard error of the mean difference**, which is an estimated population standard deviation of mean difference scores.⁶

$$s_{\bar{D}} = \frac{\tilde{s}_D}{\sqrt{n}} \quad (\text{Equation 17.4})$$

Employing Equation 17.4, the value $s_{\bar{D}} = .56$ is computed.

$$s_{\bar{D}} = \frac{1.78}{\sqrt{10}} = .56$$

Substituting $\bar{D} = 16$ and $s_{\bar{D}} = .56$ in Equation 17.1, the value $t = 2.86$ is computed.⁷

$$t = \frac{1.6}{.56} = 2.86$$

The reader should take note of the fact that the values \tilde{s}_D and $s_{\bar{D}}$, both of which are estimates of either a population standard deviation or the standard deviation of a sampling distribution, can never be a negative number. If a negative value is obtained for either of the aforementioned values, it indicates a computational error has been made.

V. Interpretation of the Test Results

The obtained value $t = 2.86$ is evaluated with **Table A2 (Table of Student's t Distribution)** in the **Appendix**. The degrees of freedom for the **t test for two dependent samples** are computed with Equation 17.5.

$$df = n - 1 \tag{Equation 17.5}$$

Employing Equation 17.5, the value $df = 10 - 1 = 9$ is computed. The tabled critical two-tailed and one-tailed .05 and .01 t values for $df = 9$ are summarized in **Table 17.2**. (For a review of the protocol for employing **Table A2**, the reader should review Section V of the **single-sample t test**.)

Table 17.2 Tabled Critical .05 and .01 t Values for $df = 9$

	$t_{.05}$	$t_{.01}$
Two-tailed values	2.26	3.25
One-tailed values	1.83	2.82

The following guidelines are employed in evaluating the null hypothesis for the **t test for two dependent samples**.

a) If the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is employed, the null hypothesis can be rejected if the obtained absolute value of t is equal to or greater than the tabled critical two-tailed value at the prespecified level of significance.

b) If the directional alternative hypothesis $H_1: \mu_1 > \mu_2$ is employed, the null hypothesis can be rejected if the sign of t is positive, and the value of t is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

c) If the directional alternative hypothesis $H_1: \mu_1 < \mu_2$ is employed, the null hypothesis can be rejected if the sign of t is negative, and the absolute value of t is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

Employing the above guidelines, the following conclusions can be reached.

The nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is supported at the .05 level, since the computed value $t = 2.86$ is greater than the tabled critical two-tailed value $t_{.05} = 2.26$. The latter alternative hypothesis, however, is not supported at the .01 level, since $t = 2.86$ is less than the tabled critical two-tailed value $t_{.01} = 3.25$.

The directional alternative hypothesis $H_1: \mu_1 > \mu_2$ is supported at both the .05 and .01 levels, since the obtained value $t = 2.86$ is a positive number that is greater than the tabled critical one-tailed values $t_{.05} = 1.83$ and $t_{.01} = 2.82$. Note that when the directional alternative hypothesis $H_1: \mu_1 > \mu_2$ is supported, it is required that $\bar{X}_1 > \bar{X}_2$.

The directional alternative hypothesis $H_1: \mu_1 < \mu_2$ is not supported, since the obtained value $t = 2.86$ is a positive number. In order for the directional alternative hypothesis $H_1: \mu_1 < \mu_2$ to be supported, the computed value of t must be a negative number (as well as the fact that the absolute value of t must be equal to or greater than the tabled critical one-tailed value at the prespecified level of significance). In order for the data to be consistent with the directional alternative hypothesis $H_1: \mu_1 < \mu_2$, it is required that $\bar{X}_1 < \bar{X}_2$.

A summary of the analysis of Example 17.1 with the **t test for two dependent samples** follows: It can be concluded that the average GSR (emotionality) score for the sexually explicit words is significantly higher than the average GSR score for the neutral words. This result can be summarized as follows (if $\alpha = .05$ is employed): $t(9) = 2.86, p < .05$.

VI. Additional Analytical Procedures for the t Test for Two Dependent Samples and/or Related Tests

1. Alternative equation for the t test for two dependent samples Equation 17.6 is an alternative equation that can be employed to compute the test statistic for the **t test for two dependent samples**.⁸

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{s_{\bar{X}_1}^2 + s_{\bar{X}_2}^2 - 2(r_{X_1 X_2})(s_{\bar{X}_1})(s_{\bar{X}_2})}} \quad (\text{Equation 17.6})$$

The computation of t with Equation 17.6 requires more computations than does Equation 17.1 (the direct difference method equation). Equation 17.6, unlike Equation 17.1, requires that the estimated population variance be computed for each of the samples (in Section VI it is noted that the latter values are required in order to evaluate the homogeneity of variance assumption of the **t test for two dependent samples**). Since a total understanding of Equation 17.6 requires an understanding of the concept of correlation, the reader may find it useful to read Section I of the **Pearson product-moment correlation coefficient (Test 28)** prior to continuing this section.

Except for the last term in the denominator of Equation 17.6 (i.e., $2(r_{X_1 X_2})(s_{\bar{X}_1})(s_{\bar{X}_2})$), the latter equation is identical to Equation 11.2 (the equation for the **t test for two independent samples** when $n_1 = n_2$). The value $r_{X_1 X_2}$ represents the coefficient of correlation between the two scores of subjects (or matched pairs of subjects) on the dependent variable. It is expected that as a result of using the same subjects in both conditions (or by employing matched subjects), a positive correlation will exist between pairs of scores (i.e., scores that are in the same row of [Table 17.1](#)). The closer the value of $r_{X_1 X_2}$ is to +1, the stronger the association between the scores of subjects on the dependent variable. (When $r = +1$, subjects who have a high score in Condition 1 will have a comparably high score in Condition 2, and subjects who have a low score in Condition 1 will have a comparably low score in Condition 2.) As the value of $r_{X_1 X_2}$ approaches +1, the value of the denominator of Equation 17.6 decreases, which will result in an increase in the absolute value computed for t . Note that if $r_{X_1 X_2} = 0$, the denominator of Equation 17.6 becomes identical to the denominator of Equation 11.2. Thus, if the scores of the n subjects under the two experimental conditions are not correlated with one another, the equation for the **t test for two dependent samples** (as represented by Equation 17.6) reduces to Equation 11.2.

The intent of the above discussion is to illustrate that one advantage of employing a design that can be evaluated with the ***t* test for two dependent samples**, as opposed to a design that is evaluated with the ***t* test for two independent samples**, is that if there is a positive correlation between pairs of scores, the former test will provide a more powerful test of an alternative hypothesis than will the latter test. The greater power associated with the ***t* test for two dependent samples** is a direct result of the lower value that will be computed for the denominator of Equation 17.6 when contrasted with the denominator that will be computed for Equation 11.2 for the same set of data. In the case of both equations, the denominator is an estimated measure of variability in a sampling distribution. By employing pairs of scores that are positively correlated with one another, the estimated variability in the sampling distribution will be less than will be the case if the scores are not correlated with one another.⁹

The computation of *t* with Equation 17.6 will now be illustrated. Note that in order to compute *t* with the latter equation, the following values are required: \bar{X}_1 , \bar{X}_2 , $s_{\bar{X}_1}$, $s_{\bar{X}_2}$, $s_{\bar{X}_1}^2$, $s_{\bar{X}_2}^2$, $r_{X_1 X_2}$. In order to compute the estimated population variances and standard deviations, the values ΣX_1^2 and ΣX_2^2 are required. The latter values are computed in Table 17.3. Employing the summary information provided in Table 17.1 and the values $\Sigma X_1^2 = 293$ and $\Sigma X_2^2 = 147$, all of the above noted values, with the exception of $r_{X_1 X_2}$, are computed.

$$\begin{aligned}\bar{X}_1 &= \frac{\Sigma X_1}{n} = \frac{47}{10} = 4.7 & \bar{X}_2 &= \frac{\Sigma X_2}{n} = \frac{31}{10} = 3.1 \\ \bar{s}_1 &= \sqrt{\frac{\Sigma X_1^2 - \frac{(\Sigma X_1)^2}{n}}{n-1}} = \sqrt{\frac{293 - \frac{(47)^2}{10}}{10-1}} = 2.83 & \bar{s}_2 &= \sqrt{\frac{\Sigma X_2^2 - \frac{(\Sigma X_2)^2}{n}}{n-1}} = \sqrt{\frac{147 - \frac{(31)^2}{10}}{10-1}} = 2.38 \\ s_{\bar{X}_1} &= \frac{\bar{s}_1}{\sqrt{n}} = \frac{2.83}{\sqrt{10}} = .89 & s_{\bar{X}_2} &= \frac{\bar{s}_2}{\sqrt{n}} = \frac{2.38}{\sqrt{10}} = .75 \\ s_{\bar{X}_1}^2 &= (.89)^2 = .79 & s_{\bar{X}_2}^2 &= (.75)^2 = .56\end{aligned}$$

Equation 17.7 is employed to compute the value $r_{X_1 X_2}$.

$$r_{X_1 X_2} = \frac{\Sigma X_1 X_2 - \frac{(\Sigma X_1)(\Sigma X_2)}{n}}{\sqrt{\left[\Sigma X_1^2 - \frac{(\Sigma X_1)^2}{n}\right]\left[\Sigma X_2^2 - \frac{(\Sigma X_2)^2}{n}\right]}} \quad (\text{Equation 17.7})$$

The only value in Equation 17.7 that is required to compute $r_{X_1 X_2}$ which has not been computed for Example 17.1, is the term $\Sigma X_1 X_2$ in the numerator. The latter value, which is computed in Table 17.3, is obtained as follows: Each subject's X_1 score is multiplied by the subject's X_2 score. The resulting score represents an $X_1 X_2$ score for the subject. The n $X_1 X_2$ scores are summed, and the resulting value represents the term $\Sigma X_1 X_2$ in Equation 17.7.

Employing Equation 17.7, the value $r_{X_1 X_2} = .78$ is computed.

$$r_{X_1 X_2} = \frac{193 - \frac{(47)(31)}{10}}{\sqrt{\left[293 - \frac{(47)^2}{10}\right]\left[147 - \frac{(31)^2}{10}\right]}} = .78$$

Table 17.3 Computation of ΣX_1^2 , ΣX_2^2 , and $\Sigma X_1 X_2$ for Example 17.1

Subject	Condition 1		Condition 2		$X_1 X_2$
	X_1	X_1^2	X_2	X_2^2	
1	9	81	8	64	72
2	2	4	2	4	4
3	1	1	3	9	3
4	4	16	2	4	8
5	6	36	3	9	18
6	4	16	0	0	0
7	7	49	4	16	28
8	8	64	5	25	40
9	5	25	4	16	20
10	1	1	0	0	0
$\Sigma X_1 = 47$		$\Sigma X_1^2 = 293$	$X_2 = 31$	$X_2^2 = 147$	$\Sigma X_1 X_2 = 193$

When the relevant values are substituted in Equation 17.6, the value $t = 2.86$ is computed (which is the same value computed for t with Equation 17.1).¹⁰ Note that the value of the numerator of Equation 17.6 is $\bar{X}_1 - \bar{X}_2 = \bar{D} = 1.6$.

$$t = \frac{4.7 - 3.1}{\sqrt{.79 + .56 - 2(.78)(.89)(.75)}} = 2.86$$

In order to illustrate that the **t test for two dependent samples** provides a more powerful test of an alternative hypothesis than the **t test for two independent samples**, the data for Example 17.1 will be evaluated with Equation 11.2 (which is the equation for the latter test). In employing Equation 11.2, the positive correlation that exists between the scores of subjects under the two experimental conditions will not be taken into account. Use of Equation 11.2 with the data for Example 17.1 assumes that in lieu of having $n = 10$ subjects, there are instead two independent groups, each group being comprised of 10 subjects. Thus, $n_1 = 10$, and the 10 X_1 scores in Table 17.1 represent the scores of the 10 subjects in Group 1, and $n_2 = 10$, and the 10 X_2 scores in Table 17.1 represent the scores of the 10 subjects in Group 2. Since the values \bar{X}_1 , \bar{X}_2 , $s_{X_1}^2$, and $s_{X_2}^2$ have already been computed, they can be substituted in Equation 11.2. When the relevant values are substituted in Equation 11.2, the value $t = 1.37$ is computed.

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{s_{X_1}^2 + s_{X_2}^2}} = \frac{4.7 - 3.1}{\sqrt{.79 + .56}} = 1.37$$

Employing Equation 11.4, the degrees of freedom for Equation 11.2 are $df = 10 + 10 - 2 = 18$. In Table A2, the tabled critical two-tailed .05 and .01 values for $df = 18$ are $t_{.05} = 2.10$ and $t_{.01} = 2.88$, and the tabled critical one-tailed .05 and .01 values are $t_{.05} = 1.73$ and $t_{.01} = 2.55$. Since the obtained value $t = 1.37$ is less than all of the aforementioned critical values, the null

hypothesis cannot be rejected, regardless of whether a nondirectional or directional alternative hypothesis is employed. Recollect that when the same set of data is evaluated with Equations 17.1/17.6, the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is supported at the .05 level and the directional alternative hypothesis $H_1: \mu_1 > \mu_2$ is supported at both the .05 and .01 levels.

Note that by employing twice the degrees of freedom, the tabled critical values employed for Equation 11.2 will always be smaller than those employed for Equations 17.1/17.6. However, if there is a reasonably high positive correlation between the pairs of scores, the lower critical values associated with the ***t* test for two independent samples** will be offset by the fact that the *t* value computed with Equation 11.2 will be substantially smaller than the value computed with Equations 17.1/17.6.

When the ***t* test for two dependent samples** is employed to evaluate a dependent samples design, it is assumed that a positive correlation exists between the scores of subjects in the two experimental conditions. It is, however, theoretically possible (although unlikely) that the two scores of subjects will be negatively correlated. If, in fact, the correlation between the X_1 and X_2 scores of subjects is negative, the value of the denominator of Equation 17.6 will actually be larger than will be the case if Equation 11.2 is employed to evaluate the same set of data (since in the denominator of Equation 17.6, if $r_{X_1 X_2}$ is a negative number, the product $2(r_{X_1 X_2})(s_{\bar{X}_1})(s_{\bar{X}_2})$ will be added to instead of subtracted from $s_{\bar{X}_1}^2 + s_{\bar{X}_2}^2$). In addition, if the correlation between the two scores is a very low positive value that is close to 0, the slight increment in the value of *t* computed with Equation 17.6 may be offset by the loss of degrees of freedom (and the consequent increase in the tabled critical *t* value), so as to allow Equation 11.2 (the ***t* test for two independent samples**) to provide a more powerful test of an alternative hypothesis than Equation 17.6 (the ***t* test for two dependent samples**).

In the unlikely event that in a dependent samples design there is a substantial negative correlation between subjects' scores in the two experimental conditions, it is very unlikely that evaluation of the data with Equation 17.6 will yield a significant result. However, the presence of a significant negative correlation, in and of itself, can certainly be of statistical importance. When a negative correlation is present, subjects who obtain a high score in one experimental condition will obtain a low score in the other experimental condition, and vice versa. The closer the negative correlation is to -1 , the more pronounced the tendency for a subjects' scores in the two conditions to be in the opposite direction. To illustrate the presence of a negative correlation, consider the following example. Assume that employing a dependent samples design, each of five subjects who serve in two experimental conditions obtains the following scores: **Subject 1** (1, 5); **Subject 2** (2, 4); **Subject 3** (3, 3); **Subject 4** (4, 2); **Subject 5** (5, 1). In this hypothetical example, it turns out that the correlation between the five pairs of scores is $r_{X_1 X_2} = -1$, which is the strongest possible negative correlation. Since, however, the mean and median value for both of the experimental conditions is equal to 3, evaluation of the data with the ***t* test for two dependent samples**, as well as the more commonly employed nonparametric procedures employed for a design involving two dependent samples (such as the **Wilcoxon matched-pairs signed-ranks test (Test 18)** and the **binomial sign test for two dependent samples (Test 19)**), will lead one to conclude there is no difference between the scores of subjects under the two conditions. This is the case, since such tests base the comparison of conditions on an actual or implied measure of central tendency. If it is assumed that in the above example the sample data accurately reflect what is true with respect to the underlying populations, it appears that the higher a subject's score in Condition 1, the lower the subject's score in Condition 2, and vice versa. In such a case, it can be argued that if the coefficient of correlation is statistically significant, that in itself can indicate the presence of a significant treatment effect (albeit an unusual one),

in that there is a significant association between the two sets of scores. The determination of whether a correlation coefficient is significant is discussed under the **Pearson product-moment correlation coefficient**, as well as in the discussion of a number of the other correlational procedures discussed in the book.¹¹

2. The equation for the t test for two dependent samples when a value for a difference other than zero is stated in the null hypothesis If in stating the null hypothesis for the **t test for two dependent samples** a researcher stipulates that the difference between μ_1 and μ_2 is some value other than zero, Equation 17.8 is employed to evaluate the null hypothesis in lieu of Equation 17.6.¹²

$$t = \frac{(\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)}{\sqrt{s_{\bar{X}_1}^2 + s_{\bar{X}_2}^2 - 2(r_{X_1 X_2})(s_{\bar{X}_1})(s_{\bar{X}_2})}} \quad \text{(Equation 17.8)}$$

When the null hypothesis is $H_0: \mu_1 = \mu_2$ (which as noted previously can also be written as $H_0: \mu_1 - \mu_2 = 0$), the value of $(\mu_1 - \mu_2)$ in Equation 17.8 reduces to zero, and thus what remains of the numerator in Equation 17.8 is $(\bar{X}_1 - \bar{X}_2)$ (which represents the numerator of Equation 17.6). In evaluating the value of t computed with Equation 17.8, the same protocol is employed that is described for evaluating a t value for the **t test for two independent samples** when the difference stated in the null hypothesis for the latter test is some value other than zero (in which case Equation 11.5 is employed to compute t).

3. Test 17a: The t test for homogeneity of variance for two dependent samples: Evaluation of the homogeneity of variance assumption of the t test for two dependent samples Prior to reading this section, the reader should review the discussion of homogeneity of variance in Section VI of the **t test for two independent samples**. As is the case with an independent samples design, in a dependent samples design the homogeneity of variance assumption evaluates whether there is evidence to indicate that an inequality exists between the variances of the populations represented by the two experimental conditions. The null and alternative hypotheses employed in evaluating the homogeneity of variance assumption are as follows:

Null hypothesis $H_0: \sigma_1^2 = \sigma_2^2$

(The variance of the population Condition 1 represents equals the variance of the population Condition 2 represents.)

Alternative hypothesis $H_1: \sigma_1^2 \neq \sigma_2^2$

(The variance of the population Condition 1 represents does not equal the variance of the population Condition 2 represents. This is a **nondirectional alternative hypothesis** and it is evaluated with a **two-tailed test**. In evaluating the homogeneity of variance assumption, a non-directional alternative hypothesis is always employed.)

The test that will be described in this section for evaluating the homogeneity of variance assumption is referred to as the **t test for homogeneity of variance for two dependent samples**. The reader should take note of the fact that the **F_{\max} test/ F test for two population variances (Test 11a)** (employed in evaluating the homogeneity of variance assumption for the **t test for two independent samples**) is not appropriate to use with a dependent samples design, since it does not take into account the correlation between subjects' scores in the two experimental conditions

(i.e., $r_{X_1 X_2}$). Equation 17.9 is the equation for the ***t* test for homogeneity of variance for two dependent samples**.

$$t = \frac{(\hat{s}_L^2 - \hat{s}_S^2)\sqrt{(n - 2)}}{\sqrt{4\hat{s}_L^2 \hat{s}_S^2(1 - r_{X_1 X_2}^2)}} \quad (\text{Equation 17.9})$$

Where: \hat{s}_L^2 is the larger of the two estimated population variances
 \hat{s}_S^2 is the smaller of the two estimated population variances

Since for Example 17.1 it has already been determined that $\hat{s}_1 = 2.83$ and $\hat{s}_2 = 2.38$, by squaring the latter values we can determine the values of the estimated population variances. Thus: $\hat{s}_1^2 = (2.83)^2 = 8.01 = \hat{s}_L^2$ and $\hat{s}_2^2 = (2.38)^2 = 5.66 = \hat{s}_S^2$. Substituting the appropriate values in Equation 17.9, the value $t = .79$ is computed.

$$t = \frac{(8.01 - 5.66)\sqrt{(10 - 2)}}{\sqrt{4(8.01)(5.66)(1 - (.78)^2)}} = .79$$

The degrees of freedom to employ for evaluating the t value computed with Equation 17.9 are computed with Equation 17.10.

$$df = n - 2 \quad (\text{Equation 17.10})$$

Employing Equation 17.10, the degrees of freedom for the analysis are $df = 10 - 2 = 8$. For $df = 8$, the tabled critical two-tailed .05 and .01 values in **Table A2** are $t_{.05} = 2.31$ and $t_{.01} = 3.35$. In order to reject the null hypothesis the obtained value of t must be equal to or greater than the tabled critical value at the prespecified level of significance. Since the value $t = .79$ is less than both of the aforementioned critical values, the null hypothesis cannot be rejected. Thus, the homogeneity of variance assumption is not violated.

There are a number of additional points that should be noted with respect to the ***t* test for homogeneity of variance for two dependent samples**.

a) Unless $\hat{s}_L^2 = \hat{s}_S^2$ (in which case $t = 0$), Equation 17.8 will always yield a positive t value. This is the case, since in the numerator of the equation the smaller variance is subtracted from the larger variance.

b) In some sources Equation 17.9 is written in the form of Equation 17.11, which employs the notation \hat{s}_1^2 and \hat{s}_2^2 in place of \hat{s}_L^2 and \hat{s}_S^2 .

$$t = \frac{(\hat{s}_1^2 - \hat{s}_2^2)\sqrt{(n - 2)}}{\sqrt{4\hat{s}_1^2 \hat{s}_2^2(1 - r_{X_1 X_2}^2)}} \quad (\text{Equation 17.11})$$

If Equation 17.11 is employed, the computed value of t can be a negative number. Specifically, t will be negative when $\hat{s}_2^2 > \hat{s}_1^2$. In point of fact, the sign of t is irrelevant, unless one is evaluating a directional alternative hypothesis. Since the homogeneity of variance assumption involves evaluation of a nondirectional alternative hypothesis, when Equation 17.11 is employed, the researcher is only interested in the absolute value of t .

c) As is the case for a test of homogeneity of variance for two independent samples, it is possible to use the ***t* test for homogeneity of variance for two dependent samples** to evaluate

a directional alternative hypothesis regarding the relationship between the variances of two populations. Thus, if a researcher specifically predicts that the variance of the population represented by Condition 1 is larger than the variance of the population represented by Condition 2 (i.e., $H_1: \sigma_1^2 > \sigma_2^2$), or that the variance of the population represented by Condition 1 is smaller than the variance of the population represented by Condition 2 (i.e., $H_1: \sigma_1^2 < \sigma_2^2$), the latter pair of directional alternative hypotheses can be evaluated with Equation 17.11. In such a case, the sign of the computed t value is relevant. If one employs Equation 17.11 to evaluate a directional alternative hypothesis, the following guidelines are employed in evaluating the null hypothesis:

1) If the directional alternative hypothesis $H_1: \sigma_1^2 > \sigma_2^2$ is employed, the null hypothesis can be rejected if the obtained absolute value of t is positive, and the value of t is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

2) If the directional alternative hypothesis $H_1: \sigma_1^2 < \sigma_2^2$ is employed, the null hypothesis can be rejected if the sign of t is negative, and the absolute value of t is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

If the directional alternative hypothesis $H_1: \sigma_1^2 > \sigma_2^2$ is evaluated for Example 17.1, the tabled critical one-tailed .05 and .01 values employed for the analysis are $t_{.05} = 1.86$ and $t_{.01} = 2.90$ (which respectively correspond to the tabled values at the 95th and 99th percentiles). Although the data are consistent with the directional alternative hypothesis $H_1: \sigma_1^2 > \sigma_2^2$, the null hypothesis cannot be rejected, since the obtained value $t = .79$ is less than the aforementioned one-tailed critical values. ($t = .79$ is obtained with Equation 17.11, since as previously noted, $\hat{s}_1^2 = \hat{s}_L^2 = 8.01$ and $\hat{s}_2^2 = \hat{s}_S^2 = 5.66$.)

d) Equation 17.12 is an alternative but equivalent form of Equation 17.11.

$$t = \frac{(F - 1)\sqrt{(n - 2)}}{2\sqrt{F(1 - r_{X_1X_2}^2)}} \quad \text{(Equation 17.12)}$$

In Equation 17.12, the value of F is computed with Equation 11.8 ($F = \hat{s}_1^2 / \hat{s}_2^2$, which is described under the **t test for two independent samples**). Substituting the appropriate values in Equation 17.12, the value $t = .79$ is computed.

$$F = \frac{8.01}{5.66} = 1.42 \quad t = \frac{(1.42 - 1)\sqrt{(10 - 2)}}{2\sqrt{(1.42)(1 - .78^2)}} = .79$$

Note that Equation 17.12 can only yield a positive t value.

e) Equation 17.13 is an alternative but equivalent form of Equation 17.9 that can only be employed to evaluate a nondirectional alternative hypothesis. Since $\hat{s}_1^2 = \hat{s}_L^2 = 8.01$ and $\hat{s}_2^2 = \hat{s}_S^2 = 5.66$, Equation 17.13 yields the value $t = .79$ (since $F_{\max} = 8.01/5.66 = 1.42$).

$$t = \frac{(F_{\max} - 1)\sqrt{(n - 2)}}{2\sqrt{F_{\max}(1 - r_{X_1X_2}^2)}} \quad \text{(Equation 17.13)}$$

Where: $F_{\max} = \hat{s}_L^2 / \hat{s}_S^2$ (which is Equation 11.6)

All of the equations noted in this section for the **t test for homogeneity of variance for two dependent samples** are based on the following two assumptions: a) The samples have been randomly drawn from the populations they represent; and b) The distribution of data in the underlying population each of the samples represents is normal. It is noted in the discussion of

homogeneity of variance in Section VI of the ***t* test for two independent samples**, that violation of the normality assumption can severely compromise the reliability of certain tests of homogeneity of variance. The ***t* test for homogeneity of variance for two dependent samples** is among those tests whose reliability can be compromised if the normality assumption is violated.

The problems associated with the use of the ***t* test for two independent samples** when the homogeneity of variance assumption is violated are also applicable to the ***t* test for two dependent samples**. Thus, if the homogeneity of variance assumption is violated, it will generally inflate the Type I error rate associated with the ***t* test for two dependent samples**. The reader should take note of the fact that when the homogeneity of variance assumption is violated with a dependent samples design, its effect on the Type I error rate will be greater than for an independent samples design. In the event the homogeneity of variance assumption is violated for a dependent samples design, either of the following strategies can be employed: a) In conducting the ***t* test for two dependent samples**, the researcher can run a more conservative test. Thus, if the researcher does not want the Type I error rate to be greater than .05, instead of employing $t_{.05}$ as the tabled critical value, she can employ $t_{.01}$ to represent the latter value; or b) In lieu of the ***t* test for two dependent samples**, a nonparametric test that does not assume homogeneity of variance can be employed to evaluate the data (such as the **Wilcoxon matched-pairs signed-ranks test**).

4. Computation of the power of the *t* test for two dependent samples and the application of Test 17b: Cohen's *d* index In this section the two methods for computing power that are described for computing the power of the ***t* test for two independent samples** will be extended to the ***t* test for two dependent samples**. Prior to reading this section, the reader may find it useful to review the discussion of power for both the **single-sample *t* test** and the ***t* test for two independent samples**.

The first procedure to be described is the graphical method which reveals the logic underlying the power computations for the ***t* test for two dependent samples**. In the discussion to follow, it will be assumed that the null hypothesis is identical to that employed for Example 17.1 (i.e., $H_0: \mu_1 - \mu_2 = 0$, which, as previously noted, is another way of writing $H_0: \mu_1 = \mu_2$). It will also be assumed that the researcher wants to evaluate the power of the ***t* test for two dependent samples** in reference to the following alternative hypothesis: $H_1: |\mu_1 - \mu_2| \geq 1.6$ (which is the difference obtained between the means of the two experimental conditions in Example 17.1). In other words, it is predicted that the absolute value of the difference between the two means is equal to or greater than 1.6. The latter alternative hypothesis is employed in lieu of $H_1: \mu_1 - \mu_2 \neq 0$ (which can also be written as $H_1: \mu_1 \neq \mu_2$), since in order to compute the power of the test, a specific value must be stated for the difference between the population means. Note that, as stated, the alternative hypothesis stipulates a nondirectional analysis, since it does not specify which of the two means will be the larger value. It will be assumed that $\alpha = .05$ is employed in the analysis.

Figure 17.1, which provides a visual summary of the power analysis, is comprised of two overlapping sampling distributions of difference scores. The distribution on the left, which will be designated as Distribution A, is a sampling distribution of difference scores that has a mean value of zero (i.e., $\mu_D = \mu_{\bar{X}_1} - \bar{X}_2 = 0$). This latter value will be represented by $\mu_{D_0} = 0$ in Figure 17.1. Distribution A represents the sampling distribution that describes the distribution of difference scores if the null hypothesis is true. The distribution on the right, which will be designated as Distribution B, is a sampling distribution of difference scores that has a mean value of 1.6 (i.e., $\mu_D = \mu_{\bar{X}_1} - \bar{X}_2 = 1.6$). This latter value will be represented by $\mu_{D_1} = 1.6$ in Figure 17.1. Distribution B represents the sampling distribution that describes the distribution of

difference scores if the alternative hypothesis is true. Each of the sampling distributions has a standard deviation that is equal to the value computed for $s_{\bar{D}} = .56$, the estimated standard error of the mean difference, since the latter value provides the best estimate of the standard deviation of the mean difference in the underlying populations.

In Figure 17.1, area (///) delineates the proportion of Distribution A that corresponds to the value $\alpha/2$, which equals .025. This is the case, since $\alpha = .05$ and a two-tailed analysis is conducted. Area (≡) delineates the proportion of Distribution B that corresponds to the probability of committing a Type II error (β). Area (\\) delineates the proportion of Distribution B that represents the power of the test (i.e., $1 - \beta$).

The procedure for computing the proportions documented in Figure 17.1 will now be described. The first step in computing the power of the test requires one to determine how large a difference there must be between the sample means in order to reject the null hypothesis. In order to do this, we algebraically transpose the terms in Equations 17.1/17.6, using $s_{\bar{D}}$ to summarize the denominator of the equation, and $t_{.05}$ (the tabled critical two-tailed .05 t value) to represent t . Thus: $\bar{X}_1 - \bar{X}_2 = (t_{.05})(s_{\bar{D}})$. By substituting the values $t_{.05} = 2.26$ and $s_{\bar{D}} = .56$ in the latter equation, we determine that the minimum required difference is $\bar{X}_1 - \bar{X}_2 = (2.26)(.56) = 1.27$ (which is represented by the notation $\bar{X}_D = 1.27$ in Figure 17.1). Thus, any difference between the two population means that is equal to or greater than 1.27 will allow the researcher to reject the null hypothesis at the .05 level.

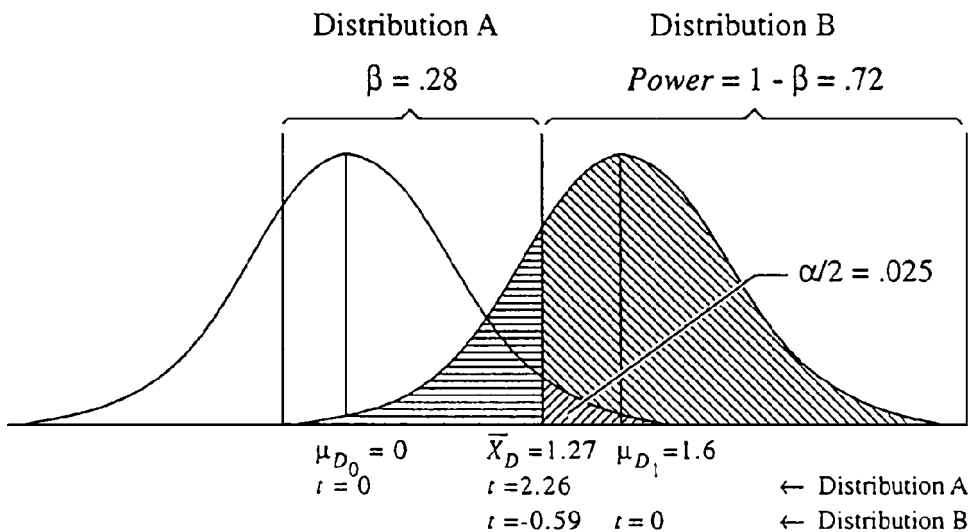


Figure 17.1 Visual Representation of Power for Example 17.1

The next step in the analysis requires one to compute the area in Distribution B that falls between the mean difference $\mu_{D_1} = 1.6$ (i.e., the mean of Distribution B) and a mean difference equal to 1.27 (represented by the notation $\bar{X}_D = 1.27$ in Figure 17.1). This is accomplished by employing Equations 17.1/17.6. In using the latter equation, the value of \bar{X}_1 is represented by 1.27 and the value of \bar{X}_2 by $\mu_{D_1} = 1.6$.

$$t = \frac{\bar{X}_1 - \bar{X}_2}{s_{\bar{D}}} = \frac{1.27 - 1.6}{.56} = -.59$$

By interpolating the values listed in [Table A2](#) for $df=9$, we determine that the proportion of Distribution B that falls between the mean and a t score of $-.59$ (which corresponds to a mean difference of 1.27) is approximately $.22$. The latter area plus the 50% of Distribution B to the right of the mean corresponds to area (\\) in Distribution B. Note that the left boundary of area (\\) is also the boundary delineating the extreme 2.5% of Distribution A (i.e., $\alpha/2 = .025$, which is the rejection zone for the null hypothesis). Since area (\\) in Distribution B overlaps the rejection zone in Distribution A, area (\\) represents the power of the test — i.e., it represents the likelihood of rejecting the null hypothesis if the alternative hypothesis is true. The power of the test is obtained by adding $.22$ and $.5$. Thus, the power of the test equals $.72$. The likelihood of committing a Type II error (β) is represented by area (\equiv), which comprises the remainder of Distribution B. The proportion of Distribution B that constitutes this latter area is determined by subtracting the value $.72$ from 1 . Thus: $\beta = 1 - .72 = .28$.

Based on the results of the power analysis, we can state that if the alternative hypothesis $H_1: |\mu_1 - \mu_2| \geq 1.6$ is true, the likelihood that the null hypothesis will be rejected is $.72$, and at the same time, there is a $.28$ likelihood that it will be retained. If the researcher considers the computed value for power too low (which in actuality should be determined prior to conducting a study), she can increase the power of the test by employing a larger sample size.

Method 2 for computing the power of the t test for two dependent samples employing Test 17b: Cohen's d index Method 2 described for computing the power of the t test for two independent samples can also be extended to the t test for two dependent samples. In using this latter method, the researcher must stipulate an **effect size** (d), which in the case of the t test for two dependent samples is computed with Equation 17.14. The effect size index computed with Equation 17.14 was developed by Cohen (1977, 1988), and is known as **Cohen's d index**. Further discussion of **Cohen's d index** can be found in Section IX (the **Appendix**) of the **Pearson product-moment correlation coefficient** under the discussion of **meta-analysis and related topics**.

$$d = \frac{|\mu_1 - \mu_2|}{\sigma_D} \quad (\text{Equation 17.14})$$

The numerator of Equation 17.14 represents the hypothesized difference between the two population means. As is the case with the graphical method described previously, when a power analysis is conducted after the mean of each sample has been obtained, the difference between the two sample means (i.e., $\bar{X}_1 - \bar{X}_2$) is employed as an estimate of the value of $|\mu_1 - \mu_2|$. In Equation 17.14, the value of σ_D represents the standard deviation of the difference scores in the population. In order to compute the power of the t test for two dependent samples, the latter value must either be known or be estimated by the researcher. If power is computed after the sample data have been collected, one can employ the value computed for \tilde{s}_D to estimate the value of σ_D . Thus, in the case of Example 17.1 we can employ $\tilde{s}_D = 1.78$ as an estimate of σ_D .

It should be noted that if one computes the power of a test prior to collecting the data (which is what a researcher should ideally do) most researchers will have great difficulty coming up with a reasonable estimate for the value of σ_D . Since a researcher is more likely to be able to estimate the values of σ_1 and σ_2 (i.e., the population standard deviation for each of the experimental conditions), if it can be assumed that $\sigma_1 = \sigma_2$ (which is true if the population variances are homogeneous), the value of σ_D can be estimated with Equation 17.15.¹³

$$\sigma_D = \sigma \sqrt{2(1 - \rho_{X_1 X_2})} \quad (\text{Equation 17.15})$$

Where: $\rho_{X_1 X_2}$ is the correlation between the two variables in the underlying populations

Since the effect size computed with Equation 17.14 is only based on population parameters, it is necessary to convert the value of d into a measure that takes into account the size of the sample (which is a relevant variable in determining the power of the test). This measure, as noted in the discussions of the **single-sample t test** and the **t test for two independent samples**, is referred to as the **noncentrality parameter**. Equation 17.16 is employed to compute the **noncentrality parameter** (δ) for the **t test for two dependent samples**.

$$\delta = d\sqrt{n} \quad \text{(Equation 17.16)}$$

The power of the **t test for two dependent samples** will now be computed using the data for Example 17.1. For purposes of illustration, it will be assumed that the minimum difference between the population means the researcher is trying to detect is the observed 1.6 point difference between the two sample means — i.e., $|\bar{X}_1 - \bar{X}_2| = |4.7 - 3.1| = 1.6 = |\mu_1 - \mu_2|$. The value of σ_D that will be employed in Equation 17.14 is $\hat{\sigma}_D = 1.78$ (which is the estimated value of the population parameter computed for the sample data). Substituting $|\mu_1 - \mu_2| = 1.6$ and $\sigma_D = 1.78$ in Equation 17.14, the value $d = .90$ is computed.

$$d = \frac{1.6}{1.78} = .90$$

Cohen (1977; 1988, pp. 24–27) has proposed the following (admittedly arbitrary) d values as criteria for identifying the magnitude of an effect size: a) A **small effect size** is one that is greater than .2 but not more than .5 standard deviation units; b) A **medium effect size** is one that is greater than .5 but not more than .8 standard deviation units; and c) A **large effect size** is greater than .8 standard deviation units. Employing Cohen's (1977, 1988) guidelines, the value $d = .90$ (which represents .90 standard deviation units) is categorized as a large effect size.

Along with the value $n = 10$, the value $d = .90$ is substituted in Equation 17.16, resulting in the value $\delta = 2.85$.

$$\delta = .90 \sqrt{10} = 2.85$$

The value $\delta = 2.85$ is evaluated with **Table A3 (Power Curves for Student's t Distribution)** in the **Appendix**. We will assume that for the example under discussion a two-tailed test is conducted with $\alpha = .05$, and thus **Table A3-C** is the appropriate set of power curves to employ for the analysis. Since there is no curve for $df = 9$, the power of the test will be based on a curve that falls between the $df = 6$ and $df = 12$ power curves. Through interpolation, the power of the **t test for two dependent samples** is determined to be approximately .72 (which is the same value that is obtained with the graphical method). Thus, by employing 10 subjects the researcher has a probability of .72 of rejecting the null hypothesis if the true difference between the population means is equal to or greater than .90 σ_D units. (which in Example 17.1 is equivalent to a 1.6 point difference between the means).

As long as a researcher knows or is able to estimate the value of σ_D , by employing trial and error she can substitute various values of n in Equation 17.16, until the computed value of δ corresponds to the desired power value for the **t test for two dependent samples** for a given effect size. This process can be facilitated by employing tables developed by Cohen (1977, 1988) which allow one to determine the minimum sample size necessary in order to achieve a specific level of power in reference to a given effect size.

5. Measure of magnitude of treatment effect for the t test for two dependent samples: Omega squared (Test 17c) Prior to reading this section, the reader should review the discussion of **magnitude of treatment effect** and the **omega squared statistic** in Section VI of the **t test for two independent samples**. In the latter discussion, it is noted that the computation of a t value only provides a researcher with information concerning the likelihood of the null hypothesis being false, but does not provide information on the magnitude of any treatment effect that is present. As noted in the discussion of the **t test for two independent samples**, a treatment effect is defined as the proportion of the variability on the dependent variable that is associated with the experimental treatments/conditions. As is the case with the **t test for two independent samples**, the magnitude of a treatment effect for the **t test for two dependent samples** can be estimated with the **omega squared** statistic ($\tilde{\omega}^2$).

In order to compute the appropriate **omega squared statistic** for the **t test for two dependent samples**, it is necessary to obtain additional values that have not been computed for Example 17.1. The latter values are obtained within the framework of conducting a **single-factor within-subjects analysis of variance (Test 24)**, which is an alternative procedure that can be employed to evaluate the data for Example 17.1 (yielding equivalent results). The derivation of the relevant values for computing **omega squared** (which are summarized in Table 17.4) is described in the discussion of the **single-factor within-subjects analysis of variance**.¹⁴

Table 17.4 Summary Table of Single-Factor Within-Subjects Analysis of Variance for Example 17.1

Source of variation	<i>SS</i>	<i>df</i>	<i>MS</i>	<i>F</i>
Between-subjects	108.8	9	12.09	
Between-conditions	12.8	1	12.80	8.11
Residual	14.2	9	1.58	
Total	135.8	19		

Keppel (1991) and Kirk (1995) note that there is disagreement with respect to which of the components derived in the analysis of variance should be employed in computing **omega squared** for a within-subjects design. One method of computing **omega squared** (which computes a value referred to as **standard omega squared**) was employed in the previous edition of this book. The latter method expresses treatment (i.e., between-conditions) variability as a proportion of the sum of all the elements that account for variability in a within-subjects design. Another method of computing **omega squared** is referred to as **partial omega squared**. The latter measure, which Keppel (1991) and Kirk (1995) view as more meaningful than **standard omega squared**, ignores between-subjects variability, and expresses treatment (i.e., between-conditions) variability as a proportion of the sum of between-conditions, and residual variability. For a set of data, the value computed for **partial omega squared** will always be larger than the value computed for **standard omega squared**.

Equation 17.17 is employed to compute **partial omega squared** ($\tilde{\omega}_p^2$). Since in Equation 17.17 k equals the number of experimental conditions, in the case of the **t test for two dependent samples** k will always equal 2.

$$\tilde{\omega}_p^2 = \frac{(k - 1)(F_{BC} - 1)}{(k - 1)(F_{BC} - 1) + nk} \quad (\text{Equation 17.17})$$

$$\tilde{\omega}_p^2 = \frac{(2 - 1)(8.11 - 1)}{(2 - 1)(8.11 - 1) + (10)(2)} = .372$$

The value $\tilde{\omega}_p^2 = .372$ computed for **partial omega squared** indicates 37.2% of the variability on the dependent variable (galvanic skin response) is associated with variability on the different levels of the independent variable (sexually explicit versus neutral words). In the previous edition of this book the value computed for **omega squared** was .08, which, as noted earlier, represents **standard omega squared**. The fact that .08 is less than .372 is consistent with the fact that the value of **standard omega squared** will always be smaller than the value of **partial omega squared**.

It is noted in an earlier discussion of **omega squared** (in Section VI of the **t test for two independent samples**) that Cohen (1977; 1988, pp. 285-288) has suggested the following (admittedly arbitrary) values, which are employed in psychology and a number of other disciplines, as guidelines for interpreting $\tilde{\omega}^2$: a) A **small effect size** is one that is greater than .0099 but not more than .0588; b) A **medium effect size** is one that is greater than .0588 but not more than .1379; and c) A **large effect size** is greater than .1379. If Cohen's (1977, 1988) guidelines are employed, the value $\tilde{\omega}_p^2 = .372$ it is categorized as a large effect size. If the value .08 computed for **standard omega squared** is employed, it is categorized as a medium effect size.

A full discussion of the computation of an **omega squared** value for a within-subjects design can be found in Section VI of the **single-factor within-subjects analysis of variance**, as well as in Keppel (1991) and Kirk (1995). The **point-biserial correlation coefficient (Test 28h)** (r_{pb}), which is another magnitude of treatment effect that can be employed for the **t test for two dependent samples**, is discussed in Section IX (the **Appendix**) of the **Pearson product-moment correlation coefficient** under the discussion of **bivariate measures of correlation that are related to the Pearson product-moment correlation coefficient**, and in the discussion of **meta-analysis and related topics**.

6. Computation of a confidence interval for the t test for two dependent samples Prior to reading this section the reader should review the discussion of the computation of confidence intervals in Section VI of the **single-sample t test** and the **t test for two independent samples**. When interval/ratio data are available for two dependent samples, a confidence interval can be computed that identifies a range of values within which one can be confident to a specified degree that the true difference lies between the two population means. Equation 17.18 is the general equation for computing the confidence interval for the difference between two dependent population means.¹⁵

$$CI_{(1 - \alpha)} = (\bar{X}_1 - \bar{X}_2) \pm (t_{\alpha})(s_{\bar{D}}) \quad \text{(Equation 17.18)}$$

Where: $t_{\alpha/2}$ represents the tabled critical two-tailed value in the t distribution, for $df = n - 1$, below which a proportion (percentage) equal to $[1 - (\alpha/2)]$ of the cases falls. If the proportion (percentage) of the distribution that falls within the confidence interval is subtracted from 1 (100%), it will equal the value of α .

Employing Equation 17.18, the 95% interval for Example 17.1 is computed below. In employing Equation 17.18, $(\bar{X}_1 - \bar{X}_2)$ represents the obtained difference between the means of the two conditions (which is the numerator of the equation used to compute the value of t), $t_{.05}$ represents the tabled critical two-tailed .05 value for $df = n - 1$, and $s_{\bar{D}}$ represents the standard error of the mean difference (which is the denominator of the equation used to compute the value of t).

$$CI_{.95} = (\bar{X}_1 - \bar{X}_2) \pm (t_{.05})(s_{\bar{D}}) = 1.6 \pm (2.26)(.56) = 1.6 \pm 1.27$$

$$.33 \leq (\mu_1 - \mu_2) \leq 2.87$$

This result indicates that the researcher can be 95% confident (or the probability is .95) that the true difference between the population means falls within the range .33 and 2.87. Specifically, it indicates that one can be 95% confident (or the probability is .95) that the mean of the population Condition 1 represents is greater than the mean of population that Condition 2 represents by at least .33 words but not by more than 2.87 words.

The 99% confidence interval for Example 17.1 will also be computed to illustrate that the range of values that define a 99% confidence interval is always larger than the range which defines a 95% confidence interval.

$$CI_{.99} = (\bar{X}_1 - \bar{X}_2) \pm (t_{.01})(s_{\bar{D}}) = 1.6 \pm (3.25)(.56) = 1.6 \pm 1.82$$

$$-.22 \leq (\mu_1 - \mu_2) \leq 3.42$$

Thus, the researcher can be 99% confident (or the probability is .99) that the true difference between the population means falls within the range $-.22$ and 3.42 . Specifically, it indicates that one can be 99% confident (or the probability is .99) that the mean of the population Condition 2 represents is no more than .22 words higher than the mean of population that Condition 1 represents, and that the mean of population that Condition 1 represents is no more than 3.42 words higher than the mean of population that Condition 2 represents. The reader should take note of the fact that the reliability of Equation 17.18 will be compromised if one or more of the assumptions of the ***t* test for two dependent samples** are saliently violated.

7. Test 17d: Sandler's A test Sandler (1955) derived a computationally simpler procedure, referred to as **Sandler's A test**, which is mathematically equivalent to the ***t* test for two dependent samples**. The test statistic for **Sandler's A test** is computed with Equation 17.19.

$$A = \frac{\sum D^2}{(\sum D)^2} \quad \text{(Equation 17.19)}$$

Note that in Equation 17.19, $\sum D$ and $\sum D^2$ are the same elements computed in [Table 17.1](#) which are employed for the direct difference method for the ***t* test for two dependent samples**. When Equation 17.19 is employed for Example 17.1, the value $A = .211$ is computed.

$$A = \frac{54}{(16)^2} = .211$$

The reader should take note of the fact that except for when $\sum D = 0$, the value of A must be a positive number. If a negative value is obtained for A , it indicates that a computational error has been made. If $\sum D = 0$ (which indicates that the means of the two conditions are equal), Equation 17.19 becomes unsolvable.

Table 17.5 Tabled Critical .05 and .01 A values for $df = 9$

	$t_{.05}$	$t_{.01}$
Two-tailed values	.276	.185
One-tailed values	.368	.213

The obtained value $A = .211$ is evaluated with **Table A12 (Table of Sandler's A Statistic)** in the **Appendix**. As is the case for the **t test for two dependent samples**, the degrees of freedom employed for **Sandler's A test** are computed with Equation 17.5. Thus, $df = 10 - 1 = 9$. The tabled critical two-tailed and one-tailed .05 and .01 values for $df = 9$ are summarized in **Table 17.5**.

The following guidelines are employed in evaluating the null hypothesis for **Sandler's A test**.

a) If the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is employed, the null hypothesis can be rejected if the obtained value of A is equal to or less than the tabled critical two-tailed value at the prespecified level of significance.

b) If the directional alternative hypothesis $H_1: \mu_1 > \mu_2$ is employed, the null hypothesis can be rejected if the sign of ΣD is positive (i.e., $\bar{X}_1 > \bar{X}_2$), and the value of A is equal to or less than the tabled critical one-tailed value at the prespecified level of significance.

c) If the directional alternative hypothesis $H_1: \mu_1 < \mu_2$ is employed, the null hypothesis can be rejected if the sign of ΣD is negative (i.e., $\bar{X}_1 < \bar{X}_2$), and the value of A is equal to or less than the tabled critical one-tailed value at the prespecified level of significance.

Employing the above guidelines, the following conclusions can be reached.

The nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is supported at the .05 level, since the computed value $A = .211$ is less than the tabled critical two-tailed value $A_{.05} = .276$. The latter alternative hypothesis, however, is not supported at the .01 level, since $A = .211$ is greater than the tabled critical two-tailed value $A_{.01} = .185$.

The directional alternative hypothesis $H_1: \mu_1 > \mu_2$ is supported at both the .05 and .01 levels, since $\Sigma D = 16$ is a positive number, and the obtained value $A = .211$ is less than the tabled critical one-tailed values $A_{.05} = .368$ and $A_{.01} = .213$.

The directional alternative hypothesis $H_1: \mu_1 < \mu_2$ is not supported, since $\Sigma D = 16$ is a positive number. In order for the directional alternative hypothesis $H_1: \mu_1 < \mu_2$ to be supported, the value of ΣD must be a negative number (as well as the fact that the computed value of A must be equal to or less than the tabled critical one-tailed value at the prespecified level of significance).

Note that the results obtained for **Sandler's A test** are identical to those obtained when the **t test for two dependent samples** is employed to evaluate Example 17.1. Equation 17.20 describes the relationship between **Sandler's A** statistic and the t value computed for the **t test for two dependent samples**.¹⁶

$$A = \frac{n - 1}{nt^2} + \frac{1}{n} \quad (\text{Equation 17.20})$$

It is demonstrated below that when $t = 2.86$ (the value computed with Equations 17.1/17.6) is substituted in Equation 17.20, it yields the value $A = .211$ computed with Equation 17.19.

$$A = \frac{10 - 1}{(10)(2.86)^2} + \frac{1}{10} = .21$$

8. Test 17e: The z test for two dependent samples There are occasions (albeit infrequent) when a researcher wants to compare the means of two dependent samples, and happens to know the variances of the two underlying populations. In such a case, the **z test for two dependent samples** should be employed to evaluate the data instead of the **t test for two dependent samples**. As is the case with the latter test, the **z test for two dependent samples** assumes that

the two samples are randomly selected from populations that have normal distributions. The effect of violation of the normality assumption on the test statistic decreases as the size of the sample employed in an experiment increases. The homogeneity of variance assumption noted for the ***t* test for two dependent samples** is not an assumption of the ***z* test for two dependent samples**.

The null and alternative hypotheses employed for the ***z* test for two dependent samples** are identical to those employed for the ***t* test for two dependent samples**. Equation 17.21 is employed to compute the test statistic for the ***z* test for two dependent samples**.¹⁷

$$z = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\sigma_{\bar{X}_1}^2 + \sigma_{\bar{X}_2}^2 - 2(r_{X_1 X_2})(\sigma_{\bar{X}_1})(\sigma_{\bar{X}_2})}} \quad (\text{Equation 17.21})$$

Where: $\sigma_{\bar{X}_i}^2 = \sigma_i^2/n$ and $\sigma_{\bar{X}_i} = \sigma_i/\sqrt{n}$

The only differences between Equation 17.21 and Equation 17.6 (the equation for the ***t* test for two dependent samples**) are: a) In the denominator of Equation 17.21, in computing the standard error of the mean for each condition, the population standard deviations σ_1 and σ_2 are employed instead of the estimated population standard deviations $\hat{\sigma}_1$ and $\hat{\sigma}_2$ (which are employed in Equation 17.6); and b) Equation 17.21 computes a *z* score which is evaluated with the normal distribution, while Equation 17.6 derives a *t* score which is evaluated with the *t* distribution.

If it is assumed that the two population variances are known for Example 17.1, and that $\sigma_1^2 = 8.01$ and $\sigma_2^2 = 5.66$, Equation 17.21 can be employed to evaluate the data. Note that the obtained value $z = 2.86$ is identical to the value that was computed for *t* when Equation 17.6 was employed.

$$z = \frac{4.7 - 3.1}{\sqrt{.79 + .56 - 2(.78)(.89)(.75)}} = 2.86$$

The obtained value $z = 2.86$ is evaluated with **Table A1 (Table of the Normal Distribution)** in the **Appendix**. In **Table A1** the tabled critical two-tailed .05 and .01 values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed .05 and .01 values are $z_{.05} = 1.65$ and $z_{.01} = 2.33$. Since the computed value $z = 2.86$ is greater than the tabled critical two-tailed values $z_{.05} = 1.96$ and $z_{.01} = 2.58$, the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is supported at both the .05 and .01 levels. Since the computed value $z = 2.86$ is a positive number which is greater than the tabled critical one-tailed values $z_{.05} = 1.65$ and $z_{.01} = 2.33$, the directional alternative hypothesis $H_1: \mu_1 > \mu_2$ is also supported at both the .05 and .01 levels.

When the same set of data are evaluated with the ***t* test for two dependent samples**, although the directional alternative hypothesis $H_1: \mu_1 > \mu_2$ is supported at both the .05 and .01 levels, the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is only supported at the .05 level. This latter fact illustrates that if the ***z* test for two dependent samples** and the ***t* test for two dependent samples** are employed to evaluate the same set of data (unless the value of *n* is extremely large), the latter test will provide a more conservative test of the null hypothesis (i.e., make it more difficult to reject H_0). This is the case, since the tabled critical values listed for the ***z* test for two dependent samples** will always correspond to the tabled critical values listed in **Table A2** for $df = \infty$ (which are the lowest tabled critical values listed for the *t* distribution).

The final part of the discussion of the ***z* test for two dependent samples** will describe a

special case of the test in which it is employed to evaluate the difference between the average performance of two conditions, when the scores of subjects are based on a binomially distributed variable. Example 17.2, which is used to illustrate this application of the test, is the dependent samples analog of Example 11.3 (which illustrates the analysis of a binomially distributed variable with the **z test for two independent samples**). The null and alternative hypotheses evaluated in Example 17.2 are identical to those evaluated in Example 17.1.

Example 17.2 *An experiment is conducted in which each of five subjects is tested for extra-sensory perception under two experimental conditions. In Condition 1 a subject listens to a relaxation training tape, after which the subject is tested while in a relaxed state of mind. In Condition 2 each subject is tested while in a normal state of mind. Assume that the order of presentation of the two experimental conditions is counterbalanced, although not completely, since to do the latter would require that an even number of subjects be employed in the study. Thus, three of the five subjects initially serve in Condition 1 followed by Condition 2, while the remaining two subjects initially serve in Condition 2 followed by Condition 1. (The concept of counterbalancing is discussed in Section VII.)*

*In each experimental condition a subject is tested for 200 trials. In each condition the researcher employs as stimuli a different list of 200 binary digits (specifically, the values 0 and 1) which have been randomly generated by a computer. On each trial, an associate of the researcher concentrates on a digit in the order it appears on the list for that condition. While the associate does this, a subject is required to guess the value of the number that is employed as the stimulus for that trial. The number of correct guesses for subjects under the two experimental conditions follow. (The first score for each subject is the number of correct responses in Condition 1, and the second score is the number of correct responses in Condition 2.): **Subject 1** (105, 90); **Subject 2** (120, 104); **Subject 3** (130, 107); **Subject 4** (115, 100); **Subject 5** (110, 99). Table 17.6 summarizes the data for the experiment.*

Table 17.6 Data for Example 17.2

Subject	Condition 1		Condition 2		$X_1 X_2$
	X_1	X_1^2	X_2	X_2^2	
1	105	11025	90	8100	9450
2	120	14400	104	10816	12480
3	130	16900	107	11449	13919
4	115	13225	100	10000	11500
5	110	12100	99	9801	10890
$\Sigma X_1 = 580$		$\Sigma X_1^2 = 67650$	$\Sigma X_2 = 500$	$\Sigma X_2^2 = 50166$	$\Sigma X_1 X_2 = 58230$
$\bar{X}_1 = \frac{580}{5} = 116$			$\bar{X}_2 = \frac{500}{5} = 100$		

Note that in Example 17.2, the five scores in each of the two experimental conditions are identical to the five scores employed in the two experimental conditions in Example 11.3. The only difference between the two examples is the order in which the scores are listed. Specifically, in Example 17.2 the scores have been arranged so that the two scores in each row (i.e., the two scores of each subject) have a high positive correlation with one another. Through use of Equation 17.7, it is demonstrated that the correlation between subjects' scores in the two experimental conditions is $r_{X_1 X_2} = .93$.

$$r_{x_1 x_2} = \frac{58230 - \frac{(580)(500)}{5}}{\sqrt{\left[67650 - \frac{(580)^2}{5}\right]\left[50166 - \frac{(500)^2}{5}\right]}} = .93$$

Example 17.2 will be evaluated with Equation 17.22, which is the form Equation 17.21 assumes when $\sigma_1^2 = \sigma_2^2$.

$$z = \frac{\bar{X}_1 - \bar{X}_2}{\sigma \sqrt{\frac{1}{m} + \frac{1}{m} - \frac{2(r_{x_1 x_2})}{m}}} \quad (\text{Equation 17.22})$$

Note that in Equation 17.22, m is employed to represent the number of subjects, since the notation n is employed with the binomial variable to designate the number of trials in which each subject is tested. Since scores on the binary guessing task described in Example 17.2 are assumed to be binomially distributed, as is the case in Example 11.3, the following is true: $n = 200$, $\pi_1 = .5$, and $\pi_2 = .5$. The computed value for the population standard deviation for the binomially distributed variable is $\sigma = \sqrt{n\pi_1\pi_2} = \sqrt{(200)(.5)(.5)} = 7.07$. (The computation of the latter values is discussed in Section I of the **binomial sign test for a single sample (Test 9)**.) When the appropriate values are substituted in Equation 17.22, the value $z = 13.52$ is computed.

$$z = \frac{116 - 100}{7.07 \sqrt{\frac{1}{5} + \frac{1}{5} - \frac{(2)(.93)}{5}}} = 13.52$$

Since the computed value $z = 13.52$ is greater than the tabled critical two-tailed values $z_{.05} = 1.96$ and $z_{.01} = 2.58$, the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is supported at both the .05 and .01 levels. Since the computed value $z = 13.52$ is a positive number that is greater than the tabled critical one-tailed values $z_{.05} = 1.65$ and $z_{.01} = 2.33$, the directional alternative hypothesis $H_1: \mu_1 > \mu_2$ is supported at both the .05 and .01 levels. Thus, it can be concluded that the average score in Condition 1 is significantly larger than the average score in Condition 2. Note that when Equation 11.17 is employed with the same set of data, it yields the value $z = 3.58$. The fact that the value $z = 13.52$ obtained with Equation 17.22 is larger than the value $z = 3.58$ obtained with Equation 11.17, illustrates that if there is a positive correlation between the scores of subjects employed in a dependent samples design, a **z test for two dependent samples** will provide a more powerful test of an alternative hypothesis than will a **z test for two independent samples** (due to the lower value of the denominator for the former test).

VII. Additional Discussion of the t Test for Two Dependent Samples

1. The use of matched subjects in a dependent samples design It is noted in Section I that the **t test for two dependent samples** can be applied to a design involving matched subjects. Matching subjects requires that a researcher initially identify one or more variables (besides the independent variable) which she believes are positively correlated with the dependent variable employed in a study. Such a variable can be employed as a matching variable. Each subject who is assigned to one of the k experimental conditions is matched with one subject in each of the

other $(k - 1)$ experimental conditions. In matching subjects it is essential that any cohort of subjects who are matched with one another are equivalent (or reasonably comparable) with respect to any matching variables employed in the study. In a design employing matched subjects there will be n cohorts (also referred to as **blocks**) of matched subjects, and within each cohort there will be k subjects. Each of the k subjects should be randomly assigned to one of the k experimental conditions/levels of the independent variable. Thus, when $k = 2$, each of the two subjects within the n pairs/cohorts will be randomly assigned to one of the two experimental conditions.

By matching subjects a researcher is able to conduct a more powerful statistical analysis than will be the case if subjects in the two conditions are not matched with one another (i.e., if an independent samples design is employed). The more similar the cohorts of subjects are on the matched variable(s), the greater the power of the statistical test. In actuality, the most extreme case of matching is when each subject is matched with him or herself, and thus serves in each of the k experimental conditions. Within this framework, the design employed for Example 17.1 can be viewed as a matched-subjects design. However, as the term matching is most commonly employed, within each row of the data summary table (i.e., [Table 17.1](#)) different subjects serve in the each of the k experimental conditions. When $k = 2$, the most extreme case of matching involving different subjects in each condition is when n pairs of identical twins are employed as subjects. By virtue of their common genetic makeup, identical twins allow an experimenter to match a subject with his or her “clone.” In Example 17.3 identical twins are employed as subjects in the same experiment described by Example 17.1. Analysis of Example 17.3 with the ***t* test for two dependent samples** yields the same result as that obtained for Example 17.1, since both examples employ the same set of data.

Example 17.3 *A psychologist conducts a study to determine whether or not people exhibit more emotionality when they are exposed to sexually explicit words than when they are exposed to neutral words. Ten sets of identical twins are employed as subjects. Within each twin pair, one of the twins is randomly assigned to Condition 1, in which the subject is shown a list of eight sexually explicit words, while the other twin is assigned to Condition 2, in which the subject is shown a list of eight neutral words. As each word is projected on the screen, a subject is instructed to say the word softly to him or herself. As a subject does this, sensors attached to the palms of the subject’s hands record galvanic skin response (GSR), which is used by the psychologist as a measure of emotionality. The psychologist computes two scores for each pair of twins to represent the emotionality score for each of the experimental conditions: **Condition 1: GSR/Explicit** — The average GSR score for the twin presented with the eight sexually explicit words; **Condition 2: GSR/Neutral** — The average GSR score for the twin presented with the eight neutral words. The GSR/Explicit and the GSR/Neutral scores of the ten pairs of twins follow. (The first score for each twin pair represents the score of the twin presented with the sexually explicit words, and the second score represents the score of the twin presented with the neutral words. The higher the score, the higher the level of emotionality.) **Twin pair 1** (9, 8); **Twin pair 2** (2, 2); **Twin pair 3** (1, 3); **Twin pair 4** (4, 2); **Twin pair 5** (6, 3); **Twin pair 6** (4, 0); **Twin pair 7** (7, 4); **Twin pair 8** (8, 5); **Twin pair 9** (5, 4); **Twin pair 10** (1, 0). Do subjects exhibit differences in emotionality with respect to the two categories of words?*

In the event $k = 3$ and a researcher wants to use identical siblings, identical triplets can be employed in a study. If $k = 4$, identical quadruplets can be used, and so on. If the critical variable(s) the researcher wants to match subjects with respect to are believed to be influenced by environmental factors, the suitability of employing identical siblings as matched subjects will be compromised to the degree that within each set of siblings the members of the set do not share common environmental experiences. Realistically, the number of available identical siblings in

a human population will be quite limited. Thus, with the exception of identical twins, it would be quite unusual to encounter a study that employs identical siblings. Because of the low frequency of identical siblings in the general population, in matching subjects a researcher may elect to employ biological relatives who share less in common with one another or employ people who are not blood relatives. Example 17.4 illustrates the latter type of matching. Analysis of Example 17.4 with the ***t* test for two dependent samples** yields the same result as that obtained for Examples 17.1 and 17.3, since all three experiments employ the same set of data.

Example 17.4 *A psychologist conducts a study to determine whether or not people exhibit more emotionality when they are exposed to sexually explicit words than when they are exposed to neutral words. Based on previous research, the psychologist has reason to believe that the following three variables are highly correlated with the dependent variable of emotionality: a) gender; b) autonomic hyperactivity (which is measured by a series of physiological measures); and c) repression/sensitization (which is measured by a pencil and paper personality test). Ten pairs of matched subjects who are identical (or very similar) on the three aforementioned variables are employed in the study. Within each pair, one person is randomly assigned to a condition in which the subject is shown a list of eight sexually explicit words, while the other person is assigned to a condition in which the subject is shown a list of eight neutral words. As each word is projected on the screen, a subject is instructed to say the word softly to him or herself. As a subject does this, sensors attached to the palms of the subject's hands record galvanic skin response (GSR), which is used by the psychologist as a measure of emotionality. The psychologist computes two scores for each pair of matched subjects to represent the emotionality score for each of the experimental conditions: **Condition 1: GSR/Explicit** — The average GSR score for the subject presented with the eight sexually explicit words; **Condition 2: GSR/Neutral** — The average GSR score for the subject presented with the eight neutral words. The GSR/Explicit and the GSR/Neutral scores of the ten pairs of subjects follow. (The first score for each pair represents the score of the person presented with the sexually explicit words, and the second score represents the score of the person presented with the neutral words. The higher the score, the higher the level of emotionality.) **Pair 1** (9, 8); **Pair 2** (2, 2); **Pair 3** (1, 3); **Pair 4** (4, 2); **Pair 5** (6, 3); **Pair 6** (4, 0); **Pair 7** (7, 4); **Pair 8** (8, 5); **Pair 9** (5, 4); **Pair 10** (1, 0). Do subjects exhibit differences in emotionality with respect to the two categories of words?*

One reason a researcher may elect to employ matched subjects (as opposed to employing each subject in all k experimental conditions) is because in many experiments it is not feasible to have a subject serve in more than one condition. Specifically, a subject's performance in one or more of the conditions might be influenced by his or her experience in one or more of the conditions that precede it. In some instances counterbalancing can be employed to control for such effects, but in other cases even counterbalancing does not provide the necessary control.

In spite of the fact that it can increase the power of a statistical analysis, matching is not commonly employed in experiments involving human subjects. The reason for this is that matching requires a great deal of time and effort on the part of a researcher. Not only is it necessary to identify one or more matching variables that are correlated with the dependent variable, but it is also necessary to identify and obtain the cooperation of a sufficient number of matched subjects to participate in an experiment. The latter does not present as much of a problem in animal research, where litter mates can be employed as matched cohorts. Example 17.5, which is evaluated in the next section, illustrates a design that employs animal litter mates as subjects.

Example 17.5 *A researcher wants to assess the relative effect of two different kinds of punishment (loud noise versus a blast of cold air) on the emotionality of mice. Five pairs of mice*

derived from five separate litters are employed as subjects. Within each pair, one of the litter mates is randomly assigned to one of two experimental conditions. During the course of the experiment each mouse is sequestered in an experimental chamber. While in the chamber, each of the five mice in Condition 1 is periodically presented with a loud noise, and each of the five mice in Condition 2 is periodically presented with a blast of cold air. The presentation of the punitive stimulus for each of the animals is generated by a machine that randomly presents the stimulus throughout the duration of the time an animal is in the chamber. The dependent variable of emotionality employed in the study is the number of times each mouse defecates while in the experimental chamber. The number of episodes of defecation for the five pairs of mice follows. (The first score represents the litter mate exposed to noise and the second score represents the litter mate exposed to cold air.) **Litter 1** (11, 11); **Litter 2** (1, 11); **Litter 3** (0, 5); **Litter 4** (2, 8); **Litter 5** (0, 4). Do subjects exhibit differences in emotionality under the different experimental conditions?

2. Relative power of the t test for two dependent samples and the t test for two independent samples Example 17.5 will be employed to illustrate that the t test for two dependent samples provides a more powerful test of an alternative hypothesis than does the t test for two independent samples. Except for the fact that it employs a dependent samples design involving matched subjects, Example 17.5 is identical to Example 11.4 (which employs an independent samples design). Both examples employ the same set of data and evaluate the same null and alternative hypotheses. The summary values for evaluating Example 17.5 with the t test for two dependent samples (using either Equation 17.1 or 17.6) are noted below. Some of the values listed can also be found in Table 11.1 (which summarizes the same set of data for analysis with the t test for two independent samples).

$$\Sigma X_1 = 14 \quad \Sigma X_1^2 = 126 \quad \Sigma X_2 = 39 \quad \Sigma X_2^2 = 347 \quad \bar{X}_1 = 2.8 \quad \bar{X}_2 = 7.8$$

$$\Sigma X_1 X_2 = 148 \quad \bar{s}_1^2 = 21.7 \quad \bar{s}_2^2 = 10.7 \quad r_{X_1 X_2} = .64$$

$$\Sigma D = -25 \quad \Sigma D^2 = 177 \quad \bar{D} = -5 \quad \bar{s}_D = 3.61 \quad s_{\bar{D}} = 1.61$$

$$t = \frac{\bar{D}}{s_{\bar{D}}} = \frac{-5}{1.61} = -3.10$$

Since $n = 5$ in Example 17.5, $df = 5 - 1 = 4$. In Table A2, for $df = 4$, the tabled critical two-tailed .05 and .01 values are $t_{.05} = 2.78$ and $t_{.01} = 4.60$, and the tabled critical one-tailed .05 and .01 values are $t_{.05} = 2.13$ and $t_{.01} = 3.75$.

The nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is supported at the .05 level, since the computed absolute value $t = 3.10$ is greater than the tabled critical two-tailed value $t_{.05} = 2.78$. It is not, however, supported at the .01 level, since the absolute value $t = 3.10$ is less than the tabled critical two-tailed value $t_{.01} = 4.60$.

The directional alternative hypothesis $H_1: \mu_1 < \mu_2$ is supported at the .05 level, since the computed value $t = -3.10$ is a negative number, and the absolute value $t = 3.10$ is greater than the tabled critical one-tailed value $t_{.05} = 2.13$. It is not, however, supported at the .01 level since the absolute value $t = 3.10$ is less than the tabled critical one-tailed value $t_{.01} = 3.75$.

The directional alternative hypothesis $H_1: \mu_1 > \mu_2$ is not supported, since the computed value $t = -3.10$ is a negative number.

Note that the absolute value $t = -3.10$ computed for Example 17.5 is substantially higher than the absolute value $t = 1.96$ computed for Example 11.4 (which has the same data as

Example 11.1) with the ***t* test for two independent samples**. In the case of Example 11.4 (as well as Example 17.5), the directional alternative hypothesis $H_1: \mu_1 < \mu_2$ is supported at the .05 level. However, the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ (which is supported at the .05 level in the case of Example 17.5) is not supported in Example 11.4 when the data are evaluated with the ***t* test for two independent samples**. The difference in the conclusions reached with the two tests reflects the fact that the ***t* test for two dependent samples** provides a more powerful test of an alternative hypothesis (assuming there is a positive correlation (which in the example under discussion is $r_{X_1X_2} = .64$) between the scores of subjects in the two experimental conditions). In closing this discussion, it is worth noting that designs involving independent samples are more commonly employed in research than designs involving dependent samples. The reason for this is that over and above the fact that a dependent samples design allows for a more powerful test of an alternative hypothesis, it presents more practical problems in its implementation (e.g., controlling for problems that might result from subjects serving in multiple conditions; the difficulty of identifying matching variables; identifying and obtaining the cooperation of an adequate number of matched subjects).

3. Counterbalancing and order effects When each of the n subjects in an experiment serves in all k experimental conditions, it is often necessary to control for the order of presentation of the conditions.¹⁸ Thus, if all n subjects are administered Condition 1 first followed by Condition 2 (or vice versa), factors such as practice or fatigue, which are a direct function of the order of presentation of the conditions, can differentially affect subjects' scores on the dependent variable. Specifically, subjects may perform better in Condition 2 due to practice effects or subjects may perform worse in Condition 2 as a result of fatigue. As noted earlier, **counterbalancing** is a procedure which allows a researcher to control for such order effects. In **complete counterbalancing** all possible orders for presenting the experimental conditions are represented an equal number of times with respect to the total number of subjects employed in a study. Thus, if a study with $n = 10$ subjects and $k = 2$ conditions is completely counterbalanced, five subjects will initially serve in Condition 1 followed by Condition 2, while the other five subjects will initially serve in Condition 2 followed by Condition 1. If the number of experimental conditions is $k = 3$, there will be $k! = 3! = 6$ possible presentation orders (i.e., 1,2,3; 1,3,2; 2,1,3; 2,3,1; 3,1,2; 3,2,1). Under such conditions a minimum of six subjects will be required in order to employ complete counterbalancing. If a researcher wants to assign two subjects to each of the presentation orders, $6 \times 2 = 12$ subjects must be employed. It should be obvious that to completely counterbalance the order of presentation of the experimental conditions, the number of subjects must equal the value of $k!$ or be some value that is evenly divisible by it.

As the number of experimental conditions increase, complete counterbalancing becomes more difficult to implement, since the number of subjects required increases substantially. Specifically, if there are $k = 5$ experimental conditions, there are $5! = 120$ presentation orders — thus requiring a minimum of 120 subjects (which can be a prohibitively large number for a researcher to use) in order that one subject serves in each of the possible presentation orders. When it is not possible to completely counterbalance the order of presentation of the conditions, alternative less complete counterbalancing procedures are available. The **Latin square design** (which is discussed in Section VII of the **single-factor within-subjects analysis of variance**) can be employed to provide **incomplete counterbalancing** (i.e., the latter design uses some but not all of the possible orders for presenting the experimental conditions). The **Latin Square design** is more likely to be considered as a reasonable option for controlling for order effects when the independent variable is comprised of many levels (and consequently it becomes prohibitive to employ complete counterbalancing).

4. Analysis of a before-after design with the t test for two dependent samples In a **before-after design** n subjects are administered a pretest on a dependent variable. After the pretest, all n subjects are exposed to the experimental treatment. Subjects are then administered a posttest on the same dependent variable. The **t test for two dependent samples** can be employed to determine if there is a significant difference between the pretest versus posttest scores of subjects. Although there are published studies that employ the **t test for two dependent samples** to evaluate the aforementioned design, it is important to note that since it lacks a control group, a **before-after design** does not allow a researcher to conclude that the experimental treatment is responsible for a significant difference. If a significant result is obtained in such a study, it only allows the researcher to conclude that there is a significant statistical association/correlation between the experimental treatment and the dependent variable. Since correlational information does not allow one to draw conclusions with regard to cause and effect, a researcher cannot conclude that the treatment is directly responsible for the observed difference. Although it is possible that the treatment is responsible for the difference, it is also possible that the difference is due to one or more other variables that intervened between the pretest and the posttest.

To modify a **before-after design** to insure adequate experimental control, it is required that two groups of subjects be employed. In such a modification, pretest and posttest scores are obtained for both groups, but only one of the groups (the experimental group) is exposed to the experimental treatment in the time period that intervenes between the pretest and the posttest. By virtue of employing a control group which is not exposed to the experimental treatment, the researcher is able to rule out the potential influence of confounding variables. Thus, order effects, as well as other factors in the environment that subjects may have been exposed to between the pretest and the posttest, can be ruled out through use of a control group. Example 17.6 illustrates a study that employs a **before-after design** without the addition of the necessary control group.

Example 17.6 *In order to assess the efficacy of electroconvulsive therapy (ECT), a psychiatrist evaluates ten clinically depressed patients before and after a series of ECT treatments. A standardized interview is used to operationalize a patient's level of depression, and on the basis of the interview each patient is assigned a score ranging from 0 to 10 with respect to his or her level of depression prior to (pretest score) and after (posttest score) the administration of ECT. The higher a patient's score, the more depressed the patient. The pretest and posttest scores of the ten patients follow: Patient 1 (9, 8); Patient 2 (2, 2); Patient 3 (1, 3); Patient 4 (4, 2); Patient 5 (6, 3); Patient 6 (4, 0); Patient 7 (7, 4); Patient 8 (8, 5); Patient 9 (5, 4); Patient 10 (1, 0). Do the data indicate that ECT is effective?*¹⁹

Since the data for Example 17.6 are identical to that employed in Example 17.1, it yields the same result. Thus, analysis of the data with the **t test for two dependent samples** indicates that there is a significant decrease in depression following the ECT. However, as previously noted, because there is no control group, the psychiatrist cannot conclude that ECT is responsible for the decrease in depression. Inclusion of a "sham" ECT group (which is analogous to a placebo group) can provide the necessary control to evaluate the impact of ECT. Such a group would be comprised of ten additional patients for whom pretest and posttest depression scores are obtained. Between the pretest and posttest, the patients in the control group undergo all of the preparations involved in ECT, but are only administered a simulated ECT treatment (i.e., they are not actually administered the shock treatment). Only by including such a control group, can one rule out the potential role of extraneous variables that might also be responsible for the lower level of depression during the posttest. An example of such an extraneous variable would be if all of the subjects who receive ECT are in psychotherapy throughout the duration of the experiment. Without a control group, a researcher cannot determine whether a lower posttest depression score

is the result of the ECT, the psychotherapy, the ECT and psychotherapy interacting with one another, or some other variable of which the researcher is unaware. By including a control group, it is assumed (although not insured) that if any extraneous variables are present, by virtue of randomly assigning subjects to groups, the groups will be equated on such variables.

When the **before-after design** is modified by the addition of the appropriate control group, the resulting design is referred to as a **pretest-posttest control group design**. Unfortunately, researchers are not in agreement with respect to what statistical analysis is most appropriate for the latter design. Among the analytical procedures that have been recommended are the following: a) The difference scores of the two groups can be contrasted with a ***t* test for two independent samples**; b) The results can be evaluated by employing a **factorial analysis of variance for a mixed design (Test 27i)**. A factorial design has two or more independent variables (which are also referred to as factors). Thus, if the appropriate control group is employed in Example 17.6, the resulting **pretest-posttest control group design** can be conceptualized as being comprised of two independent variables. One of the independent variables is represented by the ECT versus sham ECT manipulation. The second independent variable is the pretest-posttest dichotomy. In a mixed factorial design involving two factors, one of the independent variables is a between-subjects variable (i.e., different subjects serve under different levels of that independent variable). Thus, in the example under discussion, the ECT versus sham ECT manipulation represents a between-subjects independent variable. The other independent variable in a mixed factorial design is a within-subjects variable (i.e., each subject serves under all levels of that independent variable). In the example under discussion, the pretest-posttest dichotomy represents a within-subjects independent variable; and c) The **single-factor between-subjects analysis of covariance (Test 21j)** (a procedure that is discussed in Section IX (the **Addendum**) of the **single-factor between-subjects analysis of variance (Test 21)**) can also be employed to evaluate a **pretest-posttest control group design**. In conducting an analysis of covariance, the pretest scores of subjects are employed as the covariate.

VIII. Additional Example Illustrating the Use of the *t* Test for Two Dependent Samples

Example 17.7 is an additional example that can be evaluated with the ***t* test for two dependent samples**. Since Example 17.7 employs the same data as Example 17.1, it yields the same result. Note that in Example 17.7 complete counterbalancing is employed in order to control for order effects.

Example 17.7 *A study is conducted to evaluate the relative efficacy of two drugs (Clearoxin and Lesionoxin) on chronic psoriasis. Ten subjects afflicted with chronic psoriasis participate in the study. Each subject is exposed to both drugs for a six-month period, with a three-month hiatus between treatments. Five subjects are treated with Clearoxin initially, after which they are treated with Lesionoxin. The other five subjects are treated with Lesionoxin first and then with Clearoxin. The dependent variable employed in the study is a rating of the severity of a subject's lesions under the two drug conditions. The higher the rating the more severe a subject's psoriasis. The scores of the ten subjects under the two treatment conditions follow. (The first score represents the Clearoxin condition (which represents Condition 1), and the second score the Lesionoxin condition (which represents Condition 2).) Subject 1 (9, 8); Subject 2 (2, 2); Subject 3 (1, 3); Subject 4 (4, 2); Subject 5 (6, 3); Subject 6 (4, 0); Subject 7 (7, 4); Subject 8 (8, 5); Subject 9 (5, 4); Subject 10 (1, 0). Do the data indicate that subjects respond differently to the two types of medication?*

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Endnotes

1. Alternative terms that are employed in describing a **dependent samples design** are **repeated measures design, within-subjects design, treatment-by-subjects design, correlated samples design, matched-subjects design, and randomized-blocks design**. The use of the terms **blocks** within the framework of a dependent samples design is discussed in Endnote 1 of the **single-factor within-subjects analysis of variance**.
2. A study has **internal validity** to the extent that observed differences between the experimental conditions on the dependent variable can be unambiguously attributed to a manipulated independent variable. Random assignment of subjects to the different experimental conditions is the most effective way to insure **internal validity** (by eliminating the possible influence of confounding/extraneous variables). In contrast to **internal validity**, **external validity** refers to the degree to which the results of an experiment can be generalized. The results of an experiment can only be generalized to a population of subjects, as well as environmental conditions, that are comparable to those that are employed in the experiment.
3. In actuality, when galvanic skin response (which is a measure of skin resistance) is measured, the higher a subject's GSR the less emotional the subject. In Example 17.1, it is assumed that the GSR scores have been transformed so that the higher a subject's GSR score, the greater the level of emotionality.
4. An alternative but equivalent way of writing the null hypothesis is $H_0: \mu_1 - \mu_2 = 0$. The analogous alternative but equivalent ways of writing the alternative hypotheses in the order they are presented are: $H_1: \mu_1 - \mu_2 \neq 0$; $H_1: \mu_1 - \mu_2 > 0$; and $H_1: \mu_1 - \mu_2 < 0$.
5. Note that the basic structure of Equation 17.3 is the same as Equations I.8/2.1 (the equation for the estimated population standard deviation that is employed within the framework of the **single-sample *t* test**). In Equation 17.3 a standard deviation is computed

for n D scores, whereas in Equations I.8/2.1 a standard deviation is computed for n X scores.

6. The actual value that is estimated by $s_{\bar{D}}$ is $\sigma_{\bar{D}}$, which is the standard deviation of the sampling distribution of mean difference scores for the two populations. The meaning of the **standard error of the mean difference** can be best understood by considering the following procedure for generating an empirical sampling distribution of difference scores: a) Obtain n difference scores for a random sample of n subjects; b) Compute the mean difference score (\bar{D}) for the sample; and c) Repeat steps a) and b) m times. At the conclusion of this procedure one will have obtained m mean difference scores. The **standard error of the mean difference** represents the standard deviation of the m mean difference scores, and can be computed by substituting the term \bar{D} for D in Equation 17.3. Thus: $s_{\bar{D}} = \sqrt{[\sum \bar{D}^2 - ((\sum \bar{D})^2/m)]/[m - 1]}$. The standard deviation that is computed with Equation 17.4 is an estimate of $\sigma_{\bar{D}}$.
7. In order for Equation 17.1 to be soluble, there must be variability in the n difference scores. If each subject produces the same difference score, the value of $s_{\bar{D}}$ computed with Equation 17.3 will equal 0. As a result of the latter, Equation 17.4 will yield the value $s_{\bar{D}} = 0$. Since $s_{\bar{D}}$ is the denominator of Equation 17.1, when the latter value equals zero, the t test equation will be insoluble.
8. The numerator of Equation 17.6 will always equal \bar{D} (i.e., the numerator of Equation 17.1). In the same respect the denominator of Equation 17.6 will always equal $s_{\bar{D}}$ (the denominator of Equation 17.1). The denominator of Equation 17.6 can also be written as follows:

$$\sqrt{\frac{\bar{s}_1^2}{n} + \frac{\bar{s}_2^2}{n} - 2(r_{X_1X_2})\left[\frac{\bar{s}_1}{\sqrt{n}}\right]\left[\frac{\bar{s}_2}{\sqrt{n}}\right]}$$

9. Note that in the case of Example 11.1 (which is employed to illustrate the **t test for two independent samples**), it is reasonable to assume that scores in the same row of [Table 11.1](#) (which summarizes the data for the study) will not be correlated with one another (by virtue of the fact that two independent samples are employed in the study). When independent samples are employed, it is assumed that random factors determine the values of any pair of scores in the same row of a table summarizing the data, and consequently it is assumed that the correlation between pairs of scores in the same row will be equal to (or close to) 0.
10. Due to rounding off error, there may be a slight discrepancy between the value of t computed with Equations 17.1 and 17.6.
11. A noncorrelational procedure that allows a researcher to evaluate whether a treatment effect is present in the above described example is **Fisher's randomization procedure** (Fisher (1935)), which is generally categorized as a **permutation test**. The **randomization test for two independent samples (Test 12a)**, which is an example of a test that is based on **Fisher's randomization procedure**, is described in Section IX (the **Addendum**) of the **Mann-Whitney U test (Test 12)**. **Fisher's randomization procedure** requires that all possible score configurations which can be obtained for the value of the computed sum of the difference scores be determined. Upon computing the latter information, one can deter-

mine the likelihood of obtaining a configuration of scores that is equal to or more extreme than the one obtained for a set of data.

12. Equation 17.1 can be modified as follows to be equivalent to Equation 17.8:

$$t = [\bar{D} - (\mu_1 - \mu_2)]/s_{\bar{D}}.$$
13. Although Equation 17.15 is intended for use prior to collecting the data, it should yield the same value for σ_D if the values computed for the sample data are substituted in it. Thus, if $\sigma = 2.60$ (which is the average of the values $\bar{s}_1 = 2.83$ and $\bar{s}_2 = 2.38$), and $\rho_{X_1 X_2}$ (which is the population correlation coefficient estimated by the value $r_{X_1 X_2} = .78$) are substituted in Equation 17.15, the value $\sigma_D = 1.72$ is computed, which is quite close to the computed value $\bar{s}_D = 1.78$. The slight discrepancy between the two values can be attributed to the fact that the estimated population standard deviations are not identical.
14. In contrast to the ***t* test for two dependent samples** (which can only be employed with two dependent samples), the **single-factor within-subjects analysis of variance** can be used with a dependent samples design involving interval/ratio data in which there are k samples, where $k \geq 2$.
15. Note that the basic structure of Equation 17.18 is the same as Equation 11.15 (which is employed for computing a confidence interval for the ***t* test for two independent samples**), except that the latter equation employs $s_{\bar{X}_1 - \bar{X}_2}$ in place of $s_{\bar{D}}$.
16. It was noted earlier that if all n subjects obtain the identical difference score, Equations 17.1/17.6 become unsolvable. In the case of Equation 17.19, for a given value of n , if all n subjects obtain the same difference score the same A value will always be computed, regardless of the magnitude of the identical difference score obtained by each of the n subjects. If the value of A computed under such conditions is substituted in the equation $t = \sqrt{(n-1)/(An-1)}$ (which is algebraically derived from Equation 17.20), the latter equation becomes unsolvable (since the value $(An-1)$ will always equal zero). The conclusion that results from this observation is that Equation 17.19 is insensitive to the magnitude of the difference between experimental conditions when all subjects obtain the same difference score.
17. Equation 17.21 can also be written as follows:

$$z = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{\sigma_1^2}{n} + \frac{\sigma_2^2}{n} - 2(r_{X_1 X_2})\left[\frac{\sigma_1}{\sqrt{n}}\right]\left[\frac{\sigma_2}{\sqrt{n}}\right]}}$$

In instances when a researcher stipulates in the null hypothesis that the difference between the two population means is some value other than zero, the numerator of Equation 17.21 is the same as the numerator of Equation 17.8. The protocol for computing the value of the numerator is identical to that employed for Equation 17.8.

18. In Example 17.1, the order of presentation of the conditions is controlled by randomly

distributing the sexually explicit and neutral words throughout the 16 word list presented to each subject.

19. The doctor conducting the study might feel it would be unethical to employ a group of comparably depressed subjects as a control group, since patients in such a group would be deprived of a potentially beneficial treatment.

Test 18

The Wilcoxon Matched-Pairs Signed-Ranks Test (Nonparametric Test Employed with Ordinal Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test Do two dependent samples represent two different populations?

Relevant background information on test The **Wilcoxon matched-pairs signed-ranks test** (Wilcoxon (1945, 1949)) is a nonparametric procedure employed in a hypothesis testing situation involving a design with two dependent samples. Whenever one or more of the assumptions of the ***t* test for two dependent samples (Test 17)** are saliently violated, the **Wilcoxon matched-pairs signed-ranks test** (which has less stringent assumptions) may be preferred as an alternative procedure. Prior to reading the material on the **Wilcoxon matched-pairs signed-ranks test**, the reader may find it useful to review the general information regarding a dependent samples design contained in Sections I and VII of the ***t* test for two dependent samples**.

The **Wilcoxon matched-pairs signed-ranks test** is essentially an extension of the **Wilcoxon signed-ranks test (Test 6)** (which is employed for a single sample design) to a design involving two dependent samples. In order to employ the **Wilcoxon matched-pairs signed-ranks test**, it is required that each of n subjects (or n pairs of matched subjects) has two interval/ratio scores (each score having been obtained under one of the two experimental conditions). A difference score is computed for each subject (or pair of matched subjects) by subtracting a subject's score in Condition 2 from his score in Condition 1. The hypothesis evaluated with the **Wilcoxon matched-pairs signed-ranks test** is whether or not in the underlying populations represented by the samples/experimental conditions, the median of the difference scores (which will be represented by the notation θ_D) equals zero. If a significant difference is obtained, it indicates there is a high likelihood the two samples/conditions represent two different populations.

The **Wilcoxon matched-pairs signed-ranks test** is based on the following assumptions:¹
a) The sample of n subjects has been randomly selected from the population it represents; b) The original scores obtained for each of the subjects are in the format of interval/ratio data; and c) The distribution of the difference scores in the populations represented by the two samples is symmetric about the median of the population of difference scores.

As is the case for the ***t* test for two dependent samples**, in order for the **Wilcoxon matched-pairs signed-ranks test** to generate valid results, the following guidelines should be adhered to: a) To control for order effects, the presentation of the two experimental conditions should be random or, if appropriate, be counterbalanced; and b) If matched samples are employed, within each pair of matched subjects each of the subjects should be randomly assigned to one of the two experimental conditions.

As is the case with the ***t* test for two dependent samples**, the **Wilcoxon matched-pairs signed-ranks test** can also be employed to evaluate a **before-after design**. The limitations of

the **before-after design** (which are discussed in Section VII of the ***t* test for two dependent samples**) are also applicable when it is evaluated with the **Wilcoxon matched-pairs signed-ranks test**.

It should be noted that all of the other tests in this text that rank data (with the exception of the **Wilcoxon signed-ranks test** and the **Moses test for equal variability (Test 15)**), rank the original interval/ratio scores of subjects. The **Wilcoxon matched-pairs signed-ranks test**, however, does not rank the original interval/ratio scores, but instead ranks the interval/ratio difference scores of subjects (or matched pairs of subjects). For this reason, some sources categorize the **Wilcoxon matched-pairs signed-ranks test** as a test of interval/ratio data. Most sources, however (including this book), categorize the **Wilcoxon matched-pairs signed-ranks test** as a test of ordinal data, by virtue of the fact that a ranking procedure is part of the test protocol.

II. Example

Example 18.1 is identical to Example 17.1 (which is evaluated with the ***t* test for two dependent samples**). In evaluating Example 18.1 it will be assumed that the ratio data are rank-ordered, since one or more of the assumptions of the ***t* test for two dependent samples** have been saliently violated.

Example 18.1 *A psychologist conducts a study to determine whether or not people exhibit more emotionality when they are exposed to sexually explicit words than when they are exposed to neutral words. Each of ten subjects is shown a list of 16 randomly arranged words, which are projected onto a screen one at a time for a period of five seconds. Eight of the words on the list are sexually explicit and eight of the words are neutral. As each word is projected on the screen, a subject is instructed to say the word softly to him or herself. As a subject does this, sensors attached to the palms of the subject's hands record galvanic skin response (GSR), which is used by the psychologist as a measure of emotionality. The psychologist computes two scores for each subject, one score for each of the experimental conditions: **Condition 1: GSR/Explicit** — The average GSR score for the eight sexually explicit words; **Condition 2: GSR/Neutral** — The average GSR score for the eight neutral words. The GSR/Explicit and the GSR/Neutral scores of the ten subjects follow. (The higher the score, the higher the level of emotionality.) **Subject 1** (9, 8); **Subject 2** (2, 2); **Subject 3** (1, 3); **Subject 4** (4, 2); **Subject 5** (6, 3); **Subject 6** (4, 0); **Subject 7** (7, 4); **Subject 8** (8, 5); **Subject 9** (5, 4); **Subject 10** (1, 0). Do subjects exhibit differences in emotionality with respect to the two categories of words?*

III. Null versus Alternative Hypotheses

Null hypothesis $H_0: \theta_D = 0$

(In the underlying populations represented by Condition 1 and Condition 2, the median of the difference scores equals zero. With respect to the sample data, this translates into the sum of the ranks of the positive difference scores being equal to the sum of the ranks of the negative difference scores (i.e., $\sum R_+ = \sum R_-$).

Alternative hypothesis $H_1: \theta_D \neq 0$

(In the underlying populations represented by Condition 1 and Condition 2, the median of the difference scores is some value other than zero. With respect to the sample data, this translates into the sum of the ranks of the positive difference scores not being equal to the sum of the ranks

of the negative difference scores (i.e., $\sum R+ \neq \sum R-$). This is a **nondirectional alternative hypothesis** and it is evaluated with a **two-tailed test**.)

or

$$H_1: \theta_D > 0$$

(In the underlying populations represented by Condition 1 and Condition 2, the median of the difference scores is some value that is greater than zero. With respect to the sample data, this translates into the sum of the ranks of the positive difference scores being greater than the sum of the ranks of the negative difference scores (i.e., $\sum R+ > \sum R-$). The latter result indicates that the scores in Condition 1 are higher than the scores in Condition 2. This is a **directional alternative hypothesis** and it is evaluated with a **one-tailed test**.)

or

$$H_1: \theta_D < 0$$

(In the underlying populations represented by Condition 1 and Condition 2, the median of the difference scores is some value that is less than zero (i.e., a negative number). With respect to the sample data, this translates into the sum of the ranks of the positive difference scores being less than the sum of the ranks of the negative difference scores (i.e., $\sum R+ < \sum R-$). The latter result indicates that the scores in Condition 2 are higher than the scores in Condition 1. This is a **directional alternative hypothesis** and it is evaluated with a **one-tailed test**.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis is rejected.

IV. Test Computations

The data for Example 18.1 are summarized in [Table 18.1](#). Note that there are 10 subjects and that each subject has two scores.

Table 18.1 Data for Example 18.1

Subject	X_1	X_2	$D = X_1 - X_2$	Rank of $ D $	Signed rank of $ D $
1	9	8	1	2	2
2	2	2	0	—	—
3	1	3	-2	4.5	-4.5
4	4	2	2	4.5	4.5
5	6	3	3	7	7
6	4	0	4	9	9
7	7	4	3	7	7
8	8	5	3	7	7
9	5	4	1	2	2
10	1	0	1	2	2
					$\sum R+ = 40.5$
					$\sum R- = 4.5$

In [Table 18.1](#), X_1 represents each subject's score in Condition 1 (sexually explicit words) and X_2 represents each subject's score in Condition 2 (neutral words). In Column 4 of [Table 18.1](#) a D score is computed for each subject by subtracting a subject's score in Condition 2 from the subject's score in Condition 1 (i.e., $D = X_1 - X_2$). In Column 5 the D scores have

been ranked with respect to their absolute values. Since the ranking protocol employed for the **Wilcoxon matched-pairs signed-ranks test** is identical to that employed for the **Wilcoxon signed-ranks test**, the reader may find it useful to review the ranking protocol described in Section IV of the latter test. To reiterate, the following guidelines should be adhered to when ranking the difference scores for the **Wilcoxon matched-pairs signed-ranks test**.

- a) The **absolute values** of the difference scores ($|D|$) are ranked (i.e., the sign of a difference score is not taken into account).
- b) Any difference score that equals zero is not ranked. This translates into eliminating from the analysis any subject who yields a difference score of zero.
- c) When there are tied scores present in the data, the average of the ranks involved is assigned to all scores tied for a given rank.
- d) As is the case with the **Wilcoxon signed-ranks test**, when ranking difference scores for the **Wilcoxon matched-pairs signed-ranks test** it is essential that a rank of 1 be assigned to the difference score with the lowest absolute value, and that a rank of n be assigned to the difference score with the highest absolute value (where n represents the number of signed ranks — i.e., difference scores that have been ranked).²

Upon ranking the absolute values of the difference scores, the sign of each difference score is placed in front of its rank. The signed ranks of the difference scores are listed in Column 6 of [Table 18.1](#). Note that although 10 subjects participated in the experiment there are only $n = 9$ signed ranks, since Subject 2 had a difference score of zero which was not ranked. [Table 18.2](#) summarizes the rankings of the difference scores for Example 18.1.

Table 18.2 Ranking Procedure for Wilcoxon Matched-Pairs Signed-Ranks Test

Subject number	2	1	9	10	3	4	5	7	8	6
Subject’s difference score	0	1	1	1	–2	2	3	3	3	4
Absolute value of difference score	–	1	1	1	2	2	3	3	3	4
Rank of D	–	2	2	2	4.5	4.5	7	7	7	9

The sum of the ranks that have a positive sign (i.e., $\sum R+ = 40.5$) and the sum of the ranks that have a negative sign (i.e., $\sum R- = 4.5$) are recorded at the bottom of Column 6 in [Table 18.1](#). Equation 18.1 (which is identical to Equation 6.1) allows one to check the accuracy of these values. If the relationship indicated by Equation 18.1 is not obtained, it indicates an error has been made in the calculations.

$$\sum R+ + \sum R- = \frac{n(n + 1)}{2}$$

(Equation 18.1)

Employing the values $\sum R+ = 40.5$ and $\sum R- = 4.5$ in Equation 18.1, we confirm that the relationship described by the equation is true.

$$40.5 + 4.5 = \frac{(9)(10)}{2} = 45$$

V. Interpretation of the Test Results

As noted in Section III, if the sample is derived from a population in which the median of the difference scores equals zero, the values of $\sum R+$ and $\sum R-$ will be equal to one another. When $\sum R+$ and $\sum R-$ are equivalent, both of these values will equal $[n(n + 1)]/4$, which in the case of

Example 18.1 will be $[(9)(10)]/4 = 22.5$. This latter value is commonly referred to as the **expected value** of the **Wilcoxon T statistic**.

If the value of $\Sigma R+$ is significantly greater than the value of $\Sigma R-$, it indicates there is a high likelihood that Condition 1 represents a population with higher scores than the population represented by Condition 2. On the other hand, if $\Sigma R-$ is significantly greater than $\Sigma R+$, it indicates there is a high likelihood that Condition 2 represents a population with higher scores than the population represented by Condition 1. [Table 18.1](#) reveals that $\Sigma R+ = 40.5$ is greater than $\Sigma R- = 4.5$, and thus the data are consistent with the directional alternative hypothesis $H_1: \theta_D > 0$ (i.e., it indicates that subjects obtained higher scores in Condition 1 than Condition 2). The question is, however, whether the difference is significant — i.e., whether it is large enough to conclude that it is unlikely to be the result of chance.

The absolute value of the **smaller** of the two values $\Sigma R+$ versus $\Sigma R-$ is designated as the **Wilcoxon T test statistic**. Since $\Sigma R- = 4.5$ is smaller than $\Sigma R+ = 40.5$, $T = 4.5$. The T value is interpreted by employing [Table A5 \(Table of Critical \$T\$ Values for Wilcoxon's Signed-Ranks and Matched-Pairs Signed-Ranks Tests\)](#) in the **Appendix**. [Table A5](#) lists the critical two-tailed and one-tailed .05 and .01 T values in relation to the number of signed ranks in a set of data. In order to be significant, the obtained value of T must be **equal to or less than** the tabled critical T value at the prespecified level of significance.³ [Table 18.3](#) summarizes the tabled critical two-tailed and one-tailed .05 and .01 Wilcoxon T values for $n = 9$ signed ranks.

Table 18.3 Tabled Critical Wilcoxon T Values for $n = 9$ Signed Ranks

	$T_{.05}$	$T_{.01}$
Two-tailed values	5	1
One-tailed values	8	3

Since the null hypothesis can only be rejected if the computed value $T = 4.5$ is equal to or less than the tabled critical value at the prespecified level of significance, we can conclude the following.

In order for the nondirectional alternative hypothesis $H_1: \theta_D \neq 0$ to be supported, it is irrelevant whether $\Sigma R+ > \Sigma R-$ or $\Sigma R- > \Sigma R+$. In order for the result to be significant, the computed value of T must be equal to or less than the tabled critical two-tailed value at the prespecified level of significance. Since the computed value $T = 4.5$ is less than the tabled critical two-tailed .05 value $T_{.05} = 5$, the nondirectional alternative hypothesis $H_1: \theta_D \neq 0$ is supported at the .05 level. It is not, however, supported at the .01 level, since $T = 4.5$ is greater than the tabled critical two-tailed .01 value $T_{.01} = 1$.

In order for the directional alternative hypothesis $H_1: \theta_D > 0$ to be supported, $\Sigma R+$ must be greater than $\Sigma R-$. Since $\Sigma R+ > \Sigma R-$, the data are consistent with the directional alternative hypothesis $H_1: \theta_D > 0$. In order for the result to be significant, the computed value of T must be equal to or less than the tabled critical one-tailed value at the prespecified level of significance. Since the computed value $T = 4.5$ is less than the tabled critical one-tailed .05 value $T_{.05} = 8$, the directional alternative hypothesis $H_1: \theta_D > 0$ is supported at the .05 level. It is not, however, supported at the .01 level, since $T = 4.5$ is greater than the tabled critical one-tailed .01 value $T_{.01} = 3$.

In order for the directional alternative hypothesis $H_1: \theta_D < 0$ to be supported, the following two conditions must be met: a) $\Sigma R-$ must be greater than $\Sigma R+$; and b) The computed value of T must be equal to or less than the tabled critical one-tailed value at the prespecified level of significance. Since the first of these conditions is not met, the directional alternative hypothesis $H_1: \theta_D < 0$ is not supported.

A summary of the analysis of Example 18.1 with the **Wilcoxon matched-pairs signed-ranks test** follows: It can be concluded that subjects exhibited higher GSR (emotionality) scores with respect to the sexually explicit words than the neutral words.

The results obtained with the **Wilcoxon matched-pairs signed-ranks test** are reasonably consistent with those obtained when the ***t* test for two dependent samples** is employed to evaluate the same set of data. In the case of both tests, the analogous nondirectional alternative hypotheses $H_1: \theta_D \neq 0$ and $H_1: \mu_1 \neq \mu_2$ are supported, but only at the .05 level. In the case of the **Wilcoxon matched-pairs signed-ranks test**, the directional alternative hypothesis $H_1: \theta_D > 0$ is only supported at the .05 level, whereas the analogous directional alternative hypothesis $H_1: \mu_1 > \mu_2$ is supported at both the .05 and .01 levels when the data are evaluated with the ***t* test for two dependent samples**. The latter discrepancy between the two tests reflects the fact that when a parametric and nonparametric test are applied to the same set of data, the parametric test will generally provide a more powerful test of an alternative hypothesis. In most instances, however, similar conclusions will be reached if the same data are evaluated with the ***t* test for two dependent samples** and the **Wilcoxon matched-pairs signed-ranks test**.

VI. Additional Analytical Procedures for the Wilcoxon Matched-Signed-Ranks Test and/or Related Tests

1. The normal approximation of the Wilcoxon *T* statistic for large sample sizes As is the case with the **Wilcoxon signed-ranks test**, if the sample size employed in a study is relatively large, the normal distribution can be employed to approximate the Wilcoxon *T* statistic. Although sources do not agree on the value of the sample size that justifies employing the normal approximation of the Wilcoxon distribution, they generally state that it should be employed for sample sizes larger than those documented in the Wilcoxon table contained within the source. Equation 18.2 (which is identical to Equation 6.2) provides the normal approximation for Wilcoxon *T*. In the equation *T* represents the computed value of Wilcoxon *T*, which for Example 18.1 is $T = 4.5$. *n*, as noted previously, represents the number of signed ranks. Thus, in our example, $n = 9$. Note that in the numerator of Equation 18.2, the term $[n(n + 1)]/4$ represents the expected value of *T* (often summarized with the symbol T_E), which is defined in Section V. The denominator of Equation 18.2 represents the expected standard deviation of the sampling distribution of the *T* statistic.

$$z = \frac{T - \frac{n(n + 1)}{4}}{\sqrt{\frac{n(n + 1)(2n + 1)}{24}}} \quad \text{(Equation 18.2)}$$

Although Example 18.1 involves only nine signed ranks (a value most sources would view as too small to use with the normal approximation), it will be employed to illustrate Equation 18.2. The reader will see that in spite of employing Equation 18.2 with a small sample size, it will yield essentially the same result as that obtained when the exact table of the Wilcoxon distribution is employed. When the values $T = 4.5$ and $n = 9$ are substituted in Equation 18.2, the value $z = -2.13$ is computed.

$$z = \frac{4.5 - \frac{(9)(10)}{4}}{\sqrt{\frac{(9)(10)(19)}{24}}} = -2.13$$

The obtained value $z = -2.13$ is evaluated with **Table A1 (Table of the Normal Distribution)** in the **Appendix**. In **Table A1** the tabled critical two-tailed .05 and .01 values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed .05 and .01 values are $z_{.05} = 1.65$ and $z_{.01} = 2.33$.

Since the smaller of the two values $\Sigma R+$ versus $\Sigma R-$ is selected to represent T , the value of z computed with Equation 18.2 will always be a negative number (unless $\Sigma R+ = \Sigma R-$, in which case z will equal zero). This is the case, since by selecting the smaller value T will always be less than the expected value T_E . As a result of this, the following guidelines are employed in evaluating the null hypothesis.

a) If a nondirectional alternative hypothesis is employed, the null hypothesis can be rejected if the obtained absolute value of z is equal to or greater than the tabled critical two-tailed value at the prespecified level of significance.

b) When a directional alternative hypothesis is employed, one of the two possible directional alternative hypotheses will be supported if the obtained absolute value of z is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance. Which alternative hypothesis is supported depends on the prediction regarding which of the two values $\Sigma R+$ versus $\Sigma R-$ is larger. The null hypothesis can only be rejected if the directional alternative hypothesis that is consistent with the data is supported.

Employing the above guidelines, when the normal approximation is employed with Example 18.1 the following conclusions can be reached.

The nondirectional alternative hypothesis $H_1: \theta_D \neq 0$ is supported at the .05 level. This is the case, since the computed absolute value $z = 2.13$ is greater than the tabled critical two-tailed .05 value $z_{.05} = 1.96$. The nondirectional alternative hypothesis $H_1: \theta_D \neq 0$ is not supported at the .01 level, since the absolute value $z = 2.13$ is less than the tabled critical two-tailed .01 value $z_{.01} = 2.58$. This decision is consistent with the decision that is reached when the exact table of the Wilcoxon distribution is employed to evaluate the nondirectional alternative hypothesis $H_1: \theta_D \neq 0$.

The directional alternative hypothesis $H_1: \theta_D > 0$ is supported at the .05 level. This is the case, since the data are consistent with the latter alternative hypothesis (i.e., $\Sigma R+ > \Sigma R-$), and the computed absolute value $z = 2.13$ is greater than the tabled critical one-tailed .05 value $z_{.05} = 1.65$. The directional alternative hypothesis $H_1: \theta_D > 0$ is not supported at the .01 level, since the obtained absolute value $z = 2.13$ is less than the tabled critical one-tailed .01 value $z_{.01} = 2.33$. This decision is consistent with the decision that is reached when the exact table of the Wilcoxon distribution is employed to evaluate the directional alternative hypothesis $H_1: \theta_D > 0$.

The directional alternative hypothesis $H_1: \theta_D < 0$ is not supported, since the data are not consistent with the latter alternative hypothesis (which requires that $\Sigma R- > \Sigma R+$).

It should be noted that, in actuality, either $\Sigma R+$ or $\Sigma R-$ can be employed to represent the value of T in Equation 18.2. Either value will yield the same absolute value for z . The smaller of the two values will always yield a negative z value, and the larger of the two values will always yield a positive z value (which in this instance will be $z = 2.13$ if $\Sigma R+ = 40.5$ is employed to represent T). In evaluating a nondirectional alternative hypothesis the sign of z is irrelevant. In the case of a directional alternative hypothesis, one must determine whether the data are consistent with the alternative hypothesis that is stipulated. If the data are consistent, one then determines whether the absolute value of z is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

2. The correction for continuity for the normal approximation of the Wilcoxon matched-pairs signed-ranks test

As noted in the discussion of the Wilcoxon signed-ranks test, a

correction for continuity can be employed for the normal approximation of the Wilcoxon test statistic. The same correction for continuity can be applied to the **Wilcoxon matched-pairs signed-ranks test**. The correction for continuity (which results in a slight reduction in the absolute value computed for z) requires that .5 be subtracted from the absolute value of the numerator of Equation 18.2. Thus, Equation 18.3 (which is identical to Equation 6.3) represents the continuity-corrected normal approximation of the Wilcoxon test statistic.

$$z = \frac{\left| T - \frac{n(n+1)}{4} \right| - .5}{\sqrt{\frac{n(n+1)(2n+1)}{24}}} \quad (\text{Equation 18.3})$$

Employing Equation 18.3, the continuity-corrected value $z = 2.07$ is computed. Note that as a result of the absolute value conversion, the numerator of Equation 18.3 will always be a positive number, thus yielding a positive z value.

$$z = \frac{\left| 4.5 - \frac{(9)(10)}{4} \right| - .5}{\sqrt{\frac{(9)(10)(19)}{24}}} = 2.07$$

The result of the analysis with Equation 18.3 leads to the same conclusions that are reached with Equation 18.2 (i.e., when the correction for continuity is not employed). Specifically, since the absolute value $z = 2.07$ is greater than the tabled critical two-tailed .05 value $z_{.05} = 1.96$, the nondirectional alternative hypothesis $H_1: \theta_D \neq 0$ is supported at the .05 level (but not at the .01 level). Since the absolute value $z = 2.07$ is greater than the tabled critical one-tailed .05 value $z_{.05} = 1.65$, the directional alternative hypothesis $H_1: \theta_D > 0$ is supported at the .05 level (but not at the .01 level).

3. Tie correction for the normal approximation of the Wilcoxon test statistic Equation 18.4 (which is identical to Equation 6.4) is an adjusted version of Equation 18.2 that is recommended in some sources (e.g., Daniel (1990) and Marascuilo and McSweeney (1977)) when tied difference scores are present in the data. The tie correction (which is identical to the one described for the **Wilcoxon signed-ranks test**) results in a slight increase in the absolute value of z . Unless there are a substantial number of ties, the difference between the values of z computed with Equations 18.2 and 18.4 will be minimal.

$$z = \frac{T - \frac{n(n+1)}{4}}{\sqrt{\frac{n(n+1)(2n+1)}{24} - \frac{\sum t^3 - \sum t}{48}}} \quad (\text{Equation 18.4})$$

Table 18.4 illustrates the application of the tie correction with Example 18.1. In the data for Example 18.1 there are three sets of tied ranks: Set 1 involves three subjects (Subjects 1, 9, and 10); Set 2 involves two subjects (Subjects 3 and 4); Set 3 involves three subjects (Subjects 5, 7, and 8). The number of subjects involved in each set of tied ranks represents the values of

t in the third column of Table 18.4. The three t values are cubed in the last column of the table, after which the values $\sum t$ and $\sum t^3$ are computed. The appropriate values are now substituted in Equation 18.4.⁵

Table 18.4 Correction for Ties with Normal Approximation				
Subject	Rank		t	t^3
1	2	}	3	27
9	2			
10	2			
3	4.5	}	2	8
4	4.5			
5	7	}	3	27
7	7			
8	7			
6	9			
			$\Sigma t = 8$	$\Sigma t^3 = 62$

$$z = \frac{4.5 - \frac{(9)(10)}{4}}{\sqrt{\frac{(9)(10)(19)}{24} - \frac{62 - 8}{48}}} = -2.15$$

The absolute value $z = 2.15$ is slightly larger than the absolute value $z = 2.13$ obtained without the tie correction. The difference between the two methods is trivial, and in this instance, regardless of which alternative hypothesis is employed, the decision the researcher makes with respect to the null hypothesis is not affected.⁶

Conover (1980, 1999) and Daniel (1990) discuss and/or cite sources on the subject of alternative ways of handling tied difference scores. Conover (1980, 1999) also notes that in some instances retaining and ranking zero difference scores may actually provide a more powerful test of an alternative hypothesis than the more conventional method employed in this book (which eliminates zero difference scores from the data).

4. Sources for computing a confidence interval for the Wilcoxon matched-pairs signed ranks test Conover (1980, 1999), Daniel (1990), and Marascuilo and McSweeney (1977) describe procedures for computing a confidence interval for the **Wilcoxon matched-pairs signed-ranks test** — i.e., computing a range of values within which a researcher can be confident to a specified degree (or that the probability is) that a difference between two population medians falls.

VII. Additional Discussion of the Wilcoxon Matched-Pairs Signed-Ranks Test

1. Power-efficiency of the Wilcoxon matched-pairs signed-ranks test When the underlying population distributions are normal, the **asymptotic relative efficiency** (which is discussed in Section VII of the **Wilcoxon signed-ranks test**) of the **Wilcoxon matched-pairs signed-ranks test** is .955 (when contrasted with the **t test for two dependent samples**). For population distributions that are not normal, the asymptotic relative efficiency of the **Wilcoxon matched-**

pairs signed-ranks test is generally equal to or greater than 1. As a general rule, proponents of nonparametric tests take the position that when a researcher has reason to believe that the normality assumption of the ***t* test for two dependent samples** has been saliently violated, the **Wilcoxon matched-pairs signed-ranks test** provides a powerful test of the comparable alternative hypothesis.

2. Alternative nonparametric procedures for evaluating a design involving two dependent samples In addition to the **Wilcoxon matched-pairs signed-ranks test**, the **binomial sign test for two dependent samples (Test 19)** (which is described in the next chapter) can be employed to evaluate a design involving two dependent samples. Marascuilo and McSweeney (1977) describe the extension of the **van der Waerden normal-scores test for *k* independent samples (Test 23)** (Van der Waerden (1953/1953) (which is discussed later in the book) to a design involving *k* dependent samples. Normal-scores tests are procedures which involve transformation of ordinal data through use of the normal distribution. Conover (1980, 1999) notes that a normal-scores test developed by Bell and Doksum (1965) can be extended to a dependent samples design. Another procedure that can be employed with a dependent samples design is **Fisher's randomization procedure** (Fisher (1935)) (which is described in Conover (1980, 1999), Marascuilo and McSweeney (1977) and Siegel and Castellan (1988)). **The randomization test for two independent samples (Test 12a)** (which is described in Section IX (the **Addendum**) of the **Mann-Whitney *U* test (Test 12)**) illustrates the use of **Fisher's randomization procedure** with two independent samples. Additional nonparametric procedures that can be employed with a *k* dependent samples design are either discussed or referenced in Conover (1980, 1999), Daniel (1990), Hollander and Wolfe (1999), Marascuilo and McSweeney (1977), and Sheskin (1984).

VIII. Additional Examples Illustrating the Use of the Wilcoxon Matched-Pairs Signed-Ranks Test

The **Wilcoxon matched-pairs signed-ranks test** can be employed to evaluate any of the additional examples noted for the ***t* test for two dependent samples** (i.e., Examples 17.2–17.7). In all instances in which the **Wilcoxon matched-pairs signed-ranks test** is employed, difference scores are obtained for subjects (or pairs of matched subjects). All difference scores are then ranked and evaluated in accordance with the ranking protocol described in Section IV.

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Endnotes

1. Some sources note that one assumption of the **Wilcoxon matched-pairs signed-ranks test** is that the variable being measured is based on a continuous distribution. In practice, however, this assumption is often not adhered to.
2. When there are tied scores for either the lowest or highest difference scores, as a result of averaging the ordinal positions of the tied scores, the rank assigned to the lowest difference score will be some value greater than 1, and the rank assigned to the highest difference score will be some value less than n .
3. A more thorough discussion of **Table A5** can be found in Section V of the **Wilcoxon signed-ranks test**.
4. The concept of **power efficiency** is discussed in Section VII of the **Mann-Whitney U test**.
5. The term $(\sum t^3 - \sum t)$ in Equation 18.4 can also be written as $\sum_{i=1}^s (t_i^3 - t_i)$. The latter notation indicates the following: a) For each set of ties, the number of ties in the set is subtracted from the cube of the number of ties in that set; and b) the sum of all the values computed in part a) is obtained. Thus, in the example under discussion (in which there are $s = 3$ sets of ties):

$$\sum_{i=1}^s (t_i^3 - t_i) = [(3)^3 - 3] + [(2)^3 - 2] + [(3)^3 - 3] = 54$$

The computed value of 54 is the same as the corresponding value $(\sum t^3 - \sum t) = 62 - 8 = 54$ computed in Equation 18.4 through use of **Table 18.4**.

6. A correction for continuity can be used in conjunction with the tie correction by subtracting .5 from the absolute value computed for the numerator of Equation 18.4. Use of the correction for continuity will reduce the tie corrected absolute value of z .

Test 19

The Binomial Sign Test for Two Dependent Samples (Nonparametric Test Employed with Ordinal Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test Do two dependent samples represent two different populations?

Relevant background information on test The **binomial sign test for two dependent samples** is essentially an extension of the **binomial sign test for a single sample (Test 9)** to a design involving two dependent samples. Since a complete discussion of the binomial distribution (which is the distribution upon which the test is based) is contained in the discussion of the **binomial sign test for a single sample**, the reader is advised to read the material on the latter test prior to continuing this section. Whenever one or more of the assumptions of the ***t* test for two dependent samples (Test 17)** or the **Wilcoxon matched-pairs signed-ranks test (Test 18)** are saliently violated, the **binomial sign test for a two dependent samples** can be employed as an alternative procedure. The reader should review the assumptions of the aforementioned tests, as well as the information on a dependent samples design discussed in Sections I and VII of the ***t* test for two dependent samples**.

To employ the **binomial sign test for two dependent samples**, it is required that each of n subjects (or n pairs of matched subjects) has two scores (each score having been obtained under one of the two experimental conditions). The two scores are represented by the notations X_1 and X_2 . For each subject (or pair of matched subjects), a determination is made with respect to whether a subject obtains a higher score in Condition 1 or Condition 2. Based on the latter, a signed difference ($D+$ or $D-$) is assigned to each pair of scores. The sign of the difference assigned to a pair of scores will be positive if a higher score is obtained in Condition 1 (i.e., $D+$ if $X_1 > X_2$), whereas the sign of the difference will be negative if a higher score is obtained in Condition 2 (i.e., $D-$ if $X_2 > X_1$). The hypothesis the **binomial sign test for two dependent samples** evaluates is whether or not in the underlying population represented by the sample, the proportion of subjects who obtain a positive signed difference (i.e., obtain a higher score in Condition 1) is some value other than .5. If the proportion of subjects who obtain a positive signed difference (which, for the underlying population, is represented by the notation $\pi+$) is some value that is either significantly above or below .5, it indicates there is a high likelihood the two dependent samples represent two different populations.

The **binomial sign test for two dependent samples** is based on the following assumptions:¹
a) The sample of n subjects has been randomly selected from the population it represents; and b) The format of the data is such that within each pair of scores the two scores can be rank-ordered.

As is the case for the ***t* test for two dependent samples** and the **Wilcoxon matched-pairs signed-ranks test**, in order for the **binomial sign test for two dependent samples** to generate valid results, the following guidelines should be adhered to: a) To control for order effects, the presentation of the two experimental conditions should be random or, if appropriate, be

counterbalanced; and b) If matched samples are employed, within each pair of matched subjects each of the subjects should be randomly assigned to one of the two experimental conditions.

As is the case with the ***t* test for two dependent samples** and the **Wilcoxon matched-pairs signed-ranks test**, the **binomial sign test for two dependent samples** can also be employed to evaluate a **before-after design**. The limitations of the **before-after design** (which are discussed in Section VII of the ***t* test for two dependent samples**) are also applicable when it is evaluated with the **binomial sign test for two dependent samples**.

II. Example

Example 19.1 is identical to Examples 17.1 and 18.1 (which are, respectively, evaluated with the ***t* test for two dependent samples** and the **Wilcoxon matched-pairs signed-ranks test**). In evaluating Example 19.1 it will be assumed that the **binomial sign test for two dependent samples** is employed, since one or more of the assumptions of the ***t* test for two dependent samples** and the **Wilcoxon matched-pairs signed-ranks test** have been saliently violated.

Example 19.1 *A psychologist conducts a study to determine whether or not people exhibit more emotionality when they are exposed to sexually explicit words than when they are exposed to neutral words. Each of ten subjects is shown a list of 16 randomly arranged words which are projected onto a screen one at a time for a period of five seconds. Eight of the words on the list are sexually explicit in nature and eight of the words are neutral. As each word is projected on the screen, a subject is instructed to say the word softly to him or herself. As a subject does this, sensors attached to the palms of the subject's hands record galvanic skin response (GSR), which is used by the psychologist as a measure of emotionality. The psychologist computes two scores for each subject, one score for each of the experimental conditions: **Condition 1: GSR/Explicit** — The average GSR score for the eight sexually explicit words; **Condition 2: GSR/Neutral** — The average GSR score for the eight neutral words. The GSR/Explicit and the GSR/Neutral scores of the ten subjects follow. (The higher the score, the higher the level of emotionality.) **Subject 1** (9, 8); **Subject 2** (2, 2); **Subject 3** (1, 3); **Subject 4** (4, 2); **Subject 5** (6, 3); **Subject 6** (4, 0); **Subject 7** (7, 4); **Subject 8** (8, 5); **Subject 9** (5, 4); **Subject 10** (1, 0). Do subjects exhibit differences in emotionality with respect to the two categories of words?*

III. Null versus Alternative Hypotheses

Null hypothesis $H_0: \pi_+ = .5$

(In the underlying population the sample represents, the proportion of subjects who obtain a positive signed difference (i.e., a higher score in Condition 1 than Condition 2) equals .5.)

Alternative hypothesis $H_1: \pi_+ \neq .5$

(In the underlying population the sample represents, the proportion of subjects who obtain a positive signed difference (i.e., a higher score in Condition 1 than Condition 2) does not equal .5. This is a **nondirectional alternative hypothesis**, and it is evaluated with a **two-tailed test**. In order to be supported, the observed proportion of positive signed differences in the sample data (which will be represented with the notation p_+) can be either significantly larger than the hypothesized population proportion $\pi_+ = .5$ or significantly smaller than $\pi_+ = .5$.)

or

$H_1: \pi_+ > .5$

(In the underlying population the sample represents, the proportion of subjects who obtain a positive signed difference (i.e., a higher score in Condition 1 than Condition 2) is greater than .5. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. In order to be supported, the observed proportion of positive signed differences in the sample data must be significantly larger than the hypothesized population proportion $\pi_+ = .5$.)

or

$$H_1: \pi_+ < .5$$

(In the underlying population the sample represents, the proportion of subjects who obtain a positive signed difference (i.e., a higher score in Condition 1 than Condition 2) is less than .5. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. In order to be supported, the observed proportion of positive signed differences in the sample data must be significantly smaller than the hypothesized population proportion $\pi_+ = .5$.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis is rejected.²

IV. Test Computations

The data for Example 19.1 are summarized in [Table 19.1](#). Note that there are 10 subjects and that each subject has two scores.

Table 19.1 Data for Example 19.1

Subject	X_1	X_2	$D = X_1 - X_2$	Signed Difference
1	9	8	1	+
2	2	2	0	0
3	1	3	-2	-
4	4	2	2	+
5	6	3	3	+
6	4	0	4	+
7	7	4	3	+
8	8	5	3	+
9	5	4	1	+
10	1	0	1	+
				$\Sigma D_+ = 8$
				$\Sigma D_- = 1$

The following information can be derived from [Table 19.1](#): a) Eight subjects (Subjects 1, 4, 5, 6, 7, 8, 9, 10) yield a difference score with a positive sign — i.e., a positive signed difference; b) One subject (Subject 3) yields a difference score with a negative sign — i.e., a negative signed difference; and c) One subject (Subject 2) obtains the identical score in both conditions, and as a result of this yields a difference score of zero.

As is the case with the **Wilcoxon matched-pairs signed-ranks test**, in employing the **binomial sign test for two dependent samples**, any subject who obtains a zero difference score is eliminated from the data analysis. Since Subject 2 falls in this category, the size of the sample is reduced to $n = 9$, which is the same number of signed ranks employed when the **Wilcoxon matched-pairs signed-ranks test** is employed to evaluate the same set of data.

The sampling distribution of the signed differences represents a binomially distributed variable with an expected probability of .5 for each of the two mutually exclusive categories (i.e.,

positive signed difference versus negative signed difference). The logic underlying the **binomial sign test for two dependent samples** is that if the two experimental conditions represent equivalent populations, the signed differences should be randomly distributed. Thus, assuming that subjects who obtain a difference score of zero are eliminated from the analysis, if the remaining signed differences are, in fact, randomly distributed, one-half of the subjects should obtain a positive signed difference and one-half of the subjects should obtain a negative signed difference. In Example 19.1 the observed proportion of positive signed differences is $p+ = 8/9 = .89$ and the observed proportion of negative signed differences is $p- = 1/9 = .11$.

Equation 19.1 (which is identical to Equation 9.5, except for the fact that $\pi+$ and $\pi-$ are used in place of π_1 and π_2) is employed to determine the probability of obtaining $x = 8$ or more positive signed differences in a set of $n = 9$ scores.

$$P(\geq x) = \sum_{r=x}^n \binom{n}{r} (\pi+)^r (\pi-)^{(n-r)} \quad \text{(Equation 19.1)}$$

Where: $\pi+$ and $\pi-$, respectively, represent the hypothesized values for the proportion of positive and negative signed differences

n represents the number of signed differences

x represents the number of positive signed differences

In employing Equation 19.1 with Example 19.1, the following values are employed:
a) $\pi+ = .5$ and $\pi- = .5$, since if the null hypothesis is true, the proportion of positive and negative signed differences should be equal. Note that the sum of $\pi+$ and $\pi-$ must always equal 1;
b) $n = 9$, since there are 9 signed differences; and c) $x = 8$, since 8 subjects obtain a positive signed difference.

The notation $\sum_{r=x}^n$ in Equation 19.1 indicates that the probability of obtaining a value of x equal to the observed number of positive signed differences must be computed, as well as the probability for all values of x greater than the observed number of positive signed differences up through and including the value of n . Thus, in the case of Example 19.1, the binomial probability must be computed for the values $x = 8$ and $x = 9$. Equation 19.1 is employed below to compute the latter probability. The obtained value .0195 represents the likelihood of obtaining 8 or more positive signed differences in a set of $n = 9$ signed differences.

$$P(x \geq 8) = \binom{9}{8} (.5)^8 (.5)^1 + \binom{9}{9} (.5)^9 (.5)^0 = .0195$$

An even more efficient way of obtaining the probability $P(8 \text{ or } 9/9) = .0195$ is through use of **Table A7 (Table of the Binomial Distribution, Cumulative Probabilities)** in the **Appendix**. In employing **Table A7** we find the section for $n = 9$, and locate the cell that is the intersection of the row $x = 8$ and the column $\pi = .5$. The entry .0195 in that cell represents the probability of obtaining 8 or more (i.e., 8 and 9) positive signed differences, if there are a total of 9 signed differences.³

Equation 19.2 (which is identical to Equation 9.3 employed for the **binomial sign test for a single sample**, except for the fact that $\pi+$ and $\pi-$ are employed in place of π_1 and π_2) can be employed to compute each of the individual probabilities that are summed in Equation 19.1.

$$P(x) = \binom{n}{x} (\pi+)^x (\pi-)^{(n-x)} \quad \text{(Equation 19.2)}$$

Since the computation of binomial probabilities can be quite tedious, in lieu of employing Equation 19.2, **Table A6 (Table of the Binomial Distribution, Individual Probabilities)** in the **Appendix** can be used to determine the appropriate probabilities. In employing **Table A6** we find the section for $n = 9$, and locate the cell that is the intersection of the row $x = 8$ and the column $\pi = .5$. The entry .0176 in that cell represents the probability of obtaining exactly 8 positive signed differences, if there are a total of 9 signed differences. Additionally, we locate the cell that is the intersection of the row $x = 9$ and the column $\pi = .5$. The entry .0020 in that cell represents the probability of obtaining exactly 9 positive signed differences, if there are a total of 9 signed differences. Summing the latter two values yields the value $P(8 \text{ or } 9/9) = .0196$, which is the likelihood of observing 8 or 9 positive signed differences in a set of $n = 9$ signed differences.⁴ For a comprehensive discussion on the computation of binomial probabilities and the use of **Tables A6** and **A7**, the reader should review Section IV of the **binomial sign test for a single sample**.

V. Interpretation of the Test Results

The following guidelines are employed in evaluating the null hypothesis.

a) If a nondirectional alternative hypothesis is employed, the null hypothesis can be rejected if the probability of obtaining a value equal to or more extreme than x is equal to or less than $\alpha/2$ (where α represents the prespecified value of α). The reader should take note of the fact that if the proportion of positive signed differences in the data (i.e., $p+$) is greater than $\pi+ = .5$, a value that is more extreme than x will be any value that falls above the observed value of x , whereas if the proportion of positive signed differences in the data is less than $\pi+ = .5$, a value that is more extreme than x will be any value that falls below the observed value of x .

b) If a directional alternative hypothesis is employed which predicts that the underlying population proportion is above the hypothesized value $\pi+ = .5$, in order to reject the null hypothesis both of the following conditions must be met: 1) The proportion of positive signed differences must be greater than the value $\pi+ = .5$ stipulated in the null hypothesis; and 2) The probability of obtaining a value equal to or greater than x is equal to or less than the prespecified value of α .

c) If a directional alternative hypothesis is employed which predicts that the underlying population proportion is below the hypothesized value $\pi+ = .5$, in order to reject the null hypothesis both of the following conditions must be met: 1) The proportion of positive signed differences must be less than the value $\pi+ = .5$ stipulated in the null hypothesis; and 2) The probability of obtaining a value equal to or less than x is equal to or less than the prespecified value of α .

Applying the above guidelines to Example 19.1, we can conclude the following.

The nondirectional alternative hypothesis $H_1: \pi+ \neq .5$ is supported at the $\alpha = .05$ level, since the obtained probability .0195 is less than $\alpha/2 = .05/2 = .025$. The nondirectional alternative hypothesis $H_1: \pi+ \neq .5$ is not supported at the $\alpha = .01$ level, since the probability .0195 is greater than $\alpha/2 = .01/2 = .005$.⁵

The directional alternative hypothesis $H_1: \pi+ > .5$ is supported at the $\alpha = .05$ level. This is the case because: a) The data are consistent with the directional alternative hypothesis $H_1: \pi+ > .5$, since $p+ = .89$ is greater than the value $\pi+ = .5$ stated in the null hypothesis; and b) The obtained probability .0195 is less than $\alpha = .05$. The directional alternative hypothesis $H_1: \pi+ > .5$ is not supported at the $\alpha = .01$ level, since the probability .0195 is greater than $\alpha = .01$.

The directional alternative hypothesis $H_1: \pi+ < .5$ is not supported, since the data are not consistent with it. Specifically, $p+ = .89$ does not meet the requirement of being less than the value $\pi+ = .5$ stated in the null hypothesis.

A summary of the analysis of Example 19.1 with the **binomial sign test for two dependent samples** follows: It can be concluded that subjects exhibited higher GSR (emotionality) scores with respect to the sexually explicit words than the neutral words.

When the **binomial sign test for two dependent samples** and the **Wilcoxon matched-pairs signed-ranks test** are applied to the same set of data, the two tests yield identical conclusions. Specifically, both tests support the nondirectional alternative hypothesis and the directional alternative hypothesis that is consistent with the data at the .05 level. Although it is not immediately apparent from this example, as a general rule, when applied to the same data the **binomial sign test for two dependent samples** tends to be less powerful than the **Wilcoxon matched-pairs signed-ranks test**. This is the case, since by not considering the magnitude of the difference scores, the **binomial sign test for two dependent samples** employs less information than the **Wilcoxon matched-pairs signed-ranks test**. As is the case with the **Wilcoxon matched-pairs signed-ranks test**, the **binomial sign test for two dependent samples** utilizes less information than the **t test for two dependent samples**, and thus in most instances, it will provide a less powerful test of an alternative hypothesis than the latter test. In point of fact, in the case of Example 19.1, if the data are evaluated with the **t test for two dependent samples**, the directional alternative hypothesis that is consistent with the data is supported at both the .05 and .01 levels. It should be noted, however, that if the normality assumption of the **t test for two dependent samples** is saliently violated, in some instances the **binomial sign test for two dependent samples** may provide a more powerful test of an analogous alternative hypothesis.

VI. Additional Analytical Procedures for the Binomial Sign Test for Two Dependent Samples and/or Related Tests

1. The normal approximation of the binomial sign test for two dependent samples with and without a correction for continuity With large sample sizes the normal approximation for the binomial distribution (which is discussed in Section VI of the **binomial sign test for a single sample**) can provide a large sample approximation for the **binomial sign test for two dependent samples**. As a general rule, most sources recommend employing the normal approximation for sample sizes larger than those documented in the table of the binomial distribution contained in the source. Equation 19.3 (which is equivalent to Equation 9.7) is the normal approximation equation for the **binomial sign test for two dependent samples**. When a **correction for continuity** is used, Equation 19.4 (which is equivalent to Equation 9.9) is employed.⁶

$$z = \frac{x - (n)(\pi +)}{\sqrt{(n)(\pi +)(\pi -)}} \quad \text{(Equation 19.3)}$$

$$z = \frac{|x - (n)(\pi +)| - .5}{\sqrt{(n)(\pi +)(\pi -)}} \quad \text{(Equation 19.4)}$$

Although Example 19.1 involves only nine signed ranks (a value most sources would view as too small to use with the normal approximation), it will be employed to illustrate Equations 19.3 and 19.4. The reader will see that in spite of employing the normal approximation with a small sample size, it yields essentially the same results as those obtained with the exact binomial probabilities.

Employing Equation 19.3, the value $z = 2.33$ is computed.

$$z = \frac{8 - (9)(.5)}{\sqrt{(9)(.5)(.5)}} = 2.33$$

Employing Equation 19.4, the value $z = 2.00$ is computed.

$$z = \frac{|8 - (9)(.5)| - .5}{\sqrt{(9)(.5)(.5)}} = 2.00$$

The obtained z values are evaluated with **Table A1 (Table of the Normal Distribution)** in the **Appendix**. In **Table A1** the tabled critical two-tailed .05 and .01 values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed .05 and .01 values are $z_{.05} = 1.65$ and $z_{.01} = 2.33$. The following guidelines are employed in evaluating the null hypothesis.

a) If a nondirectional alternative hypothesis is employed, the null hypothesis can be rejected if the obtained absolute value of z is equal to or greater than the tabled critical two-tailed value at the prespecified level of significance.

b) If a directional alternative hypothesis is employed, only the directional alternative hypothesis that is consistent with the data can be supported. With respect to the latter alternative hypothesis, the null hypothesis can be rejected if the obtained absolute value of z is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

Employing the above guidelines, we can conclude the following.

Since the value $z = 2.33$ computed with Equation 19.3 is greater than the tabled critical two-tailed value $z_{.05} = 1.96$ but less than the tabled critical two-tailed value $z_{.01} = 2.58$, the nondirectional alternative hypothesis $H_1: \pi \neq .5$ is supported, but only at the .05 level. Since the value $z = 2.33$ is greater than the tabled critical one-tailed value $z_{.05} = 1.65$ and equal to the tabled critical one-tailed value $z_{.01} = 2.33$, the directional alternative hypothesis $H_1: \pi > .5$ is supported at both the .05 and .01 levels. Note that when the exact binomial probabilities are employed, both the nondirectional alternative hypothesis $H_1: \pi \neq .5$ and the directional alternative hypothesis $H_1: \pi > .5$ are supported, but in both instances, only at the .05 level.

When the correction for continuity is employed, the value $z = 2.00$ computed with Equation 19.4 is greater than the tabled critical two-tailed value $z_{.05} = 1.96$ but less than the tabled critical two-tailed value $z_{.01} = 2.58$. Thus, the nondirectional alternative hypothesis $H_1: \pi \neq .5$ is only supported at the .05 level. Since the value $z = 2.00$ is greater than the tabled critical one-tailed value $z_{.05} = 1.65$ but less than the tabled critical one-tailed value $z_{.01} = 2.33$, the directional alternative hypothesis $H_1: \pi > .5$ is also supported, but only at the .05 level. The results with the correction for continuity are identical to those obtained when the exact binomial probabilities are employed. Note that the continuity-corrected normal approximation provides a more conservative test of the null hypothesis than does the uncorrected normal approximation.

The **chi-square goodness-of-fit test (Test 8)** (either with or without the correction for continuity) can also be employed to provide a large sample approximation of the **binomial sign test for two dependent samples**. The **chi-square goodness-of-fit test**, which evaluates the relationship between the observed and expected frequencies in the two categories (i.e., positive signed difference versus negative signed difference), will yield a result that is equivalent to that obtained with the normal approximation. The computed chi-square value will equal the square of the z value derived with the normal approximation.

Equation 8.2 is employed for the chi-square analysis, without using a correction for continuity. Equation 8.6 is the continuity-corrected equation. **Table 19.2** summarizes the analysis of Example 19.1 with Equation 8.2.

Table 19.2 Chi-Square Summary Table for Example 19.1

Cell	O_i	E_i	$(O_i - E_i)$	$(O_i - E_i)^2$	$\frac{(O_i - E_i)^2}{E_i}$
Positive signed differences	8	4.5	3.5	12.25	2.72
Negative signed differences	1	4.5	-3.5	12.25	2.72
	$\Sigma O_i = 9$	$\Sigma E_i = 9$	$\Sigma(O_i - E_i) = 0$		$\chi^2 = 5.44$

In Table 19.2, the expected frequency $E_i = 4.5$ for each cell is computed by multiplying the hypothesized population proportion for the cell (.5 for both cells) by $n = 9$. Since $k = 2$, the degrees of freedom employed for the chi-square analysis are $df = k - 1 = 2$. The obtained value $\chi^2 = 5.44$ is evaluated with Table A4 (Table of the Chi-Square Distribution) in the Appendix. For $df = 1$, the tabled critical .05 and .01 chi-square values are $\chi^2_{.05} = 3.84$ (which corresponds to the chi-square value at the 95th percentile) and $\chi^2_{.01} = 6.63$ (which corresponds to the chi-square value at the 99th percentile). Since the obtained value $\chi^2 = 5.44$ is greater than $\chi^2_{.05} = 3.84$ but less than $\chi^2_{.01} = 6.63$, the nondirectional alternative hypothesis $H_1: \pi+ \neq .5$ is supported, but only at the .05 level. Since $\chi^2 = 5.44$ is greater than the tabled critical one-tailed .05 value $\chi^2_{.05} = 2.71$ (which corresponds to the chi-square value at the 90th percentile) and the tabled critical one-tailed .01 value $\chi^2_{.01} = 5.43$ (which corresponds to the chi-square value at the 98th percentile), the directional alternative hypothesis $H_1: \pi+ > .5$ is supported at both the .05 and .01 levels.⁷ The aforementioned conclusions are identical to those reached when Equation 19.3 is employed.

As noted previously, if the z value obtained with Equation 19.3 is squared, it will always equal the chi-square value computed for the same data. Thus, in the current example where $z = 2.33$ and $\chi^2 = 5.44$, $(2.33)^2 = 5.43$.⁸

Equation 8.6 (which, as noted previously, is the continuity-corrected equation for the **chi-square goodness-of-fit test**) is employed below, and yields an equivalent result to that obtained with Equation 19.4. In employing Equation 8.6, the value $(|O_i - E_i| - .5) = 3$ is employed for each cell. Thus:

$$\chi^2 = \sum_{i=1}^k \left[\frac{(|O_i - E_i| - .5)^2}{E_i} \right] = \frac{(3)^2}{4.5} + \frac{(3)^2}{4.5} = 4$$

Note that the obtained value $\chi^2 = 4$ is equal to the square of the value $z = 2.00$ obtained with Equation 19.4. Since $\chi^2 = 4$ is greater than $\chi^2_{.05} = 3.84$ but less than $\chi^2_{.01} = 6.63$, the nondirectional alternative hypothesis $H_1: \pi+ \neq .5$ is supported, but only at the .05 level. Since $\chi^2 = 4$ is greater than the tabled critical one-tailed .05 value $\chi^2_{.05} = 2.71$ but less than the tabled critical one-tailed .01 value $\chi^2_{.01} = 5.43$, the directional alternative hypothesis $H_1: \pi+ > .5$ is also supported at only the .05 level. The aforementioned conclusions are identical to those reached when Equation 19.4 is employed.

2. Computation of a confidence interval for the binomial sign test for two dependent samples Equation 19.5 (which is equivalent to Equation 8.5, except for the fact that $p+$, $p-$, and $\pi+$ are employed in place of p_1 , p_2 , and π_1) can be used to compute a confidence interval for the **binomial sign test for two dependent samples**. Since Equation 19.5 is based on the normal approximation, it should be employed with large sample sizes. It will, however, be used here with

the data for Example 19.1. The 95% confidence interval computed with Equation 19.5 estimates the proportion of positive signed differences in the underlying population.

$$\left[p^{+} - z_{(\alpha/2)} \sqrt{\frac{(p^{+})(p^{-})}{n}} \right] \leq \pi^{+} \leq \left[p^{+} + z_{(\alpha/2)} \sqrt{\frac{(p^{+})(p^{-})}{n}} \right] \quad (\text{Equation 19.5})$$

Employing the values computed for Example 19.1, Equation 19.5 is employed to compute the 95% confidence interval.

$$\left[.89 - (1.96) \sqrt{\frac{(.89)(.11)}{9}} \right] \leq \pi^{+} \leq \left[.89 + (1.96) \sqrt{\frac{(.89)(.11)}{9}} \right]$$

$$\pi^{+} = .89 \pm .204$$

$$.686 \leq \pi^{+} \leq 1.094$$

Thus, the researcher can be 95% confident (or the probability is .95) that the true proportion of positive signed differences in the underlying population is a value between .686 and 1.094. Obviously, since a proportion cannot be greater than 1, the range of values identified by the confidence interval will fall between .686 and 1.

It should be noted that the above method for computing a confidence interval ignores the presence of any zero difference scores. Consequently, the range of values computed for the confidence interval assumes there are no zero difference scores in the underlying population. If, in fact, there are zero difference scores in the population, the above computed confidence interval only identifies proportions that are relevant to the total number of cases in the population that are not zero difference scores. In point of fact, when one or more zero difference scores are present in the sample data, a researcher may want to assume that zero difference scores are present in the underlying population. If the researcher makes such an assumption and employs the sample data to estimate the proportion of zero difference scores in the population, the value employed for p^{+} in Equation 19.5 will represent the number of positive signed differences in the sample divided by the total number of scores in the sample, including any zero difference scores. Thus, in the case of Example 19.1, the value $p^{+} = 8/10 = .8 = .8$ is computed by dividing 8 (the number of positive signed differences) by $n = 10$. The value p^{-} in Equation 19.5 will no longer represent just the negative signed differences, but will represent all signed differences that are not positive (i.e., both negative signed differences and zero difference scores). Thus, in the case of Example 19.1, $p^{-} = 2/10 = .2$, since there is one negative signed difference and one zero difference score. If the values $n = 10$, $p^{+} = .8$, and $p^{-} = .2$ are employed in Equation 19.5, the confidence interval $.552 \leq \pi^{+} \leq 1.048$ is computed.

$$\left[.8 - (1.96) \sqrt{\frac{(.8)(.2)}{10}} \right] \leq \pi^{+} \leq \left[.8 + (1.96) \sqrt{\frac{(.8)(.2)}{10}} \right]$$

$$\pi^{+} = .8 \pm .248$$

$$.552 \leq \pi^{+} \leq 1.048$$

Thus, the researcher can be 95% confident (or the probability is .95) that the true proportion of positive signed differences in the underlying population is a value between .552 and 1.048. Since, as noted earlier, a proportion cannot be greater than 1, the range identified by

the confidence interval will fall between .552 and 1. If the researcher wants to employ the same method for computing a confidence interval for the proportion of minus signed differences in the population (i.e., π_-), the product $z_{(\alpha/2)}\sqrt{[(p^+)(p^-)]/n}$ is added to and subtracted from $p^- = .1$. The values $p^- = 1/10 = .1$ and $p^+ = 9/10 = .9$ are employed in the confidence interval equation, since there is one negative signed difference and nine signed differences that are not negative (i.e., eight positive signed differences and one zero difference score).

3. Sources for computing the power of the binomial sign test for two dependent samples, and comments on asymptotic relative efficiency of the test Cohen (1977, 1988) has developed a statistic called the **g index** that can be employed to compute the power of the **binomial sign test for a single sample** when $H_0: \pi_i = .5$ is evaluated. The latter effect size index can be generalized to compute the power of the **binomial sign test for two dependent samples**. The **g index** represents the distance in units of proportion from the value .50. The equation Cohen (1977, 1988) employs for the **g index** is $g = P - .50$, where P represents the hypothesized value of the population proportion stated in the alternative hypothesis — in this instance it is assumed that the researcher has stated a specific value in the alternative hypothesis as an alternative to the value that is stipulated in the null hypothesis.

Cohen (1977; 1988, Ch. 5) has derived tables that allow a researcher, through use of the **g index**, to determine the appropriate sample size to employ if one wants to test a hypothesis about the distance of a proportion from the value .5 at a specified level of power. Cohen (1977; 1988, pp. 147–150) has proposed the following (admittedly arbitrary) g values as criteria for identifying the magnitude of an effect size: a) A **small effect size** is one that is greater than .05 but not more than .15; b) A **medium effect size** is one that is greater than .15 but not more than .25; and c) A **large effect size** is greater than .25.

Marascuilo and McSweeney (1977) note that if the underlying population distribution is normal, the **asymptotic relative efficiency** (which is discussed in Section VII of the **Wilcoxon signed-ranks test (Test 6)**) of the **binomial sign test** is .637, in contrast to an asymptotic relative efficiency of .955 for the **Wilcoxon matched-pairs signed-ranks test** (with both asymptotic relative efficiencies being in reference to the **t test for two dependent samples**). When the underlying population distribution is not normal, in most cases, the asymptotic relative efficiency of the **Wilcoxon matched-pairs signed-ranks test** will be higher than the analogous value for the **binomial sign test for two dependent samples**.

VII. Additional Discussion of the Binomial Sign Test for Two Dependent Samples

1. The problem of an excessive number of zero difference scores When there is an excessive number of subjects who have a zero difference score in a set of data, a substantial amount of information is sacrificed if the **binomial sign test for two dependent samples** is employed to evaluate the data. Under such conditions, it is advisable to evaluate the data with the **t test for two dependent samples** (assuming the interval/ratio scores of subjects are available). If one or more of the assumptions of the latter test are saliently violated, the alpha level employed for the **t test** should be adjusted.

2. Equivalency of the Friedman two-way analysis variance by ranks and the binomial sign test for two dependent samples when $k = 2$ In Section VII of the **Friedman two-way analysis of variance by ranks (Test 25)**, it is demonstrated that when there are two dependent samples and there are no zero difference scores, the latter test (which can be employed for two or more

dependent samples) is equivalent to the chi-square approximation of the **binomial sign test for two dependent samples** (i.e., it will yield the same chi-square value computed with Equation 8.2). When employing the **Friedman two-way analysis of variance by ranks** with two dependent samples, the two scores of each subject (or pair of matched subjects) are rank-ordered. The data for Example 19.1 can be expressed in a rank-order format, if for each subject a rank of 1 is assigned to the lower of the two scores and a rank of 2 is assigned to the higher score (or vice versa). If a researcher only has such rank-order information, it is still possible to assign a signed difference to each subject, since the ordering of a subject's two ranks provides sufficient information to determine whether the difference between the two scores of a subject would yield a positive or negative value if the interval/ratio scores of the subject were available. Consequently, under such conditions one can still conduct the **binomial sign test for two dependent samples**. On the other hand, if a researcher only has the sort of rank-order information noted above, one will not be able to evaluate the data with either the ***t* test for two dependent samples** or the **Wilcoxon matched-pairs signed-ranks test**, since the latter two tests require the interval/ ratio scores of subjects.

VIII. Additional Examples Illustrating the Use of the Binomial Sign Test for Two Dependent Samples

The **binomial sign test for two dependent samples** can be employed with any of the additional examples noted for the ***t* test for two dependent samples** and the **Wilcoxon matched-pairs signed-ranks test**. In each of the examples, a signed difference must be computed for each subject (or pair of matched subjects). The signed differences are then evaluated employing the protocol for the **binomial sign test for two dependent samples**.

References

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Endnotes

1. Some sources note that one assumption of the **binomial sign test for two dependent samples** is that the variable being measured is based on a continuous distribution. In practice, however, this assumption is often not adhered to.

2. Another way of stating the null hypothesis is that in the underlying population the sample represents, the proportion of subjects who obtain a positive signed difference is equal to the proportion of subjects who obtain a negative signed difference. The null and alternative hypotheses can also be stated with respect to the proportion of people in the population who obtain a higher score in Condition 2 than Condition 1, thus yielding a negative difference score. The notation π^- represents the proportion of the population who yield a difference with a negative sign (referred to as a negative signed difference). Thus, $H_0: \pi^- = .5$ can be employed as the null hypothesis, and the following nondirectional and directional alternative hypotheses can be employed: $H_1: \pi^- \neq .5$; $H_1: \pi^- > .5$; $H_1: \pi^- < .5$.
3. It is also the likelihood of obtaining 8 or 9 negative signed differences in a set of 9 signed differences.
4. Due to rounding off protocol, the value computed with Equation 19.1 will be either .0195 or .0196, depending upon whether one employs [Table A6](#) or [Table A7](#).
5. An equivalent way of determining whether or not the result is significant is by doubling the value of the cumulative probability obtained from [Table A7](#). In order to reject the null hypothesis, the resulting value must not be greater than the value of α . Since $2 \times .0195 = .039$ is less than $\alpha = .05$, we confirm that the nondirectional alternative hypothesis is supported when $\alpha = .05$. Since .039 is greater than $\alpha = .01$, it is not supported at the .01 level.
6. Equations 9.6 and 9.8 are respectively alternate but equivalent forms of Equations 19.3 and 19.4. Note that in Equations 9.6–9.9, π_1 and π_2 are employed in place of π^+ and π^- to represent the two population proportions.
7. A full discussion of the protocol for determining one-tailed chi-square values can be found in Section VII of the **chi-square goodness-of-fit test**.
8. The minimal discrepancy is the result of rounding off error.

Test 20

The McNemar Test

(Nonparametric Test Employed with Categorical/Nominal Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test Do two dependent samples represent two different populations?

Relevant background information on test It is recommended that before reading the material on the **McNemar test**, the reader review the general information on a dependent samples design contained in Sections I and VII of the ***t* test for two dependent samples (Test 17)**. The **McNemar test** (McNemar, 1947) is a nonparametric procedure for categorical data employed in a hypothesis testing situation involving a design with two dependent samples. In actuality, the **McNemar test** is a special case of the **Cochran *Q* test (Test 26)**, which can be employed to evaluate a k dependent samples design involving categorical data, where $k \geq 2$. The **McNemar test** is employed to evaluate an experiment in which a sample of n subjects (or n pairs of matched subjects) is evaluated on a dichotomous dependent variable (i.e., scores on the dependent variable must fall within one of two mutually exclusive categories). The **McNemar test** assumes that each of the n subjects (or n pairs of matched subjects) contributes two scores on the dependent variable. The test is most commonly employed to analyze data derived from the two types of experimental designs described below.

a) The **McNemar test** can be employed to evaluate categorical data obtained in a **true experiment** (i.e., an experiment involving a manipulated independent variable).¹ In such an experiment, the two scores of each subject (or pair of matched subjects) represent a subject's responses under the two levels of the independent variable (i.e., the two experimental conditions). A significant result allows the researcher to conclude there is a high likelihood the two experimental conditions represent two different populations. As is the case with the ***t* test for two dependent samples**, the **Wilcoxon matched-pairs signed-ranks test (Test 18)**, and the **binomial sign test for two dependent samples (Test 19)**, when the **McNemar test** is employed to evaluate the data for a **true experiment**, in order for the test to generate valid results, the following guidelines should be adhered to: 1) In order to control for order effects, the presentation of the two experimental conditions should be random or, if appropriate, be counter-balanced; and 2) If matched samples are employed, within each pair of matched subjects each of the subjects should be randomly assigned to one of the two experimental conditions.

b) The **McNemar test** can be employed to evaluate a **before–after design** (which is described in Section VII of the ***t* test for two dependent samples**). In applying the **McNemar test** to a **before–after design**, n subjects are administered a pretest on a dichotomous dependent variable. Following the pretest, all of the subjects are exposed to an experimental treatment, after which they are administered a posttest on the same dichotomous dependent variable. The hypothesis evaluated with a **before–after design** is whether or not there is a significant difference between the pretest and posttest scores of subjects on the dependent variable. The reader is

advised to review the discussion of the **before–after design** in Section VII of the ***t* test for two dependent samples**, since the limitations noted for the design also apply when it is evaluated with the **McNemar test**.

The 2×2 table depicted in Table 20.1 summarizes the **McNemar test** model. The entries for Cells *a*, *b*, *c*, and *d* in Table 20.1 represent the number of subjects/observations in each of four possible categories that can be employed to summarize the two responses of a subject (or matched pair of subjects) on a dichotomous dependent variable. Each of the four response category combinations represents the number of subjects/observations whose response in Condition 1/Pretest falls in the response category for the row in which the cell falls, and whose response in Condition 2/Posttest falls in the response category for the column in which the cell falls. Thus, the entry in Cell *a* represents the number of subjects who respond in Response category 1 in both Condition 1/Pretest and Condition 2/Posttest. The entry in Cell *b* represents the number of subjects who respond in Response category 1 in Condition 1/Pretest and in Response category 2 in Condition 2/Posttest. The entry in Cell *c* represents the number of subjects who respond in Response category 2 in Condition 1/Pretest and in Response category 1 in Condition 2/Posttest. The entry in Cell *d* represents the number of subjects who respond in Response category 2 in both Condition 1/Pretest and Condition 2/Posttest.

Table 20.1 Model for the McNemar Test

		Condition 2/Posttest		Row sums
		Response category 1	Response category 2	
Condition 1/Pretest	Response category 1	<i>a</i>	<i>b</i>	$a + b = n_1$
	Response category 2	<i>c</i>	<i>d</i>	$c + d = n_2$
Column sums		$a + c$	$b + d$	n

The **McNemar test** is based on the following assumptions: a) The sample of *n* subjects has been randomly selected from the population it represents; b) Each of the *n* observations in the contingency table is independent of the other observations; c) The scores of subjects are in the form of a dichotomous categorical measure involving two mutually exclusive categories; and d) Most sources state that the **McNemar test** should not be employed with extremely small sample sizes. Although the chi-square distribution is generally employed to evaluate the **McNemar test** statistic, in actuality the latter distribution is used to provide an approximation of the exact sampling distribution which is, in fact, the binomial distribution. When the sample size is small, in the interest of accuracy, the exact binomial probability for the data should be computed. Sources do not agree on the minimum acceptable sample size for computing the **McNemar test** statistic (i.e., using the chi-square distribution). Some sources endorse the use of a correction for continuity with small sample sizes (discussed in Section VI), in order to insure that the computed chi-square value provides a more accurate estimate of the exact binomial probability.

II. Examples

Since, as noted in Section I, the **McNemar test** is employed to evaluate a **true experiment** and a **before–after design**, two examples, each representing one of the aforementioned designs, will be presented in this section. Since the two examples employ identical data, they will result in the same conclusion with respect to the null hypothesis. Example 20.1 describes a **true experiment** and Example 20.2 describes a study that employs a **before–after design**.

Example 20.1 A psychologist wants to compare a drug for treating enuresis (bed-wetting) with a placebo. One hundred enuretic children are administered both the drug (Endurin) and a placebo in a double blind study conducted over a six month period. During the duration of the study, each child has six drug and six placebo treatments, with each treatment lasting one week. To insure that there are no carryover effects from one treatment to another, during the week following each treatment a child is not given either the drug or the placebo. The order of presentation of the 12 treatment periods for each child is randomly determined. The dependent variable in the study is a parent's judgement with respect to whether or not a child improves under each of the two experimental conditions. Table 20.2 summarizes the results of the study. Do the data indicate the drug was effective?

Table 20.2 Summary of Data for Example 20.1

		Favorable response to drug		Row sums
		Yes	No	
Favorable response to placebo	Yes	10	13	23
	No	41	36	77
Column sums		51	49	100

Note that the data in Table 20.2 indicate the following: a) 10 subjects respond favorably to both the drug and the placebo; b) 13 subjects do not respond favorably to the drug but do respond favorably to the placebo; c) 41 subjects respond favorably to the drug but do not respond favorably to the placebo; and d) 36 subjects do not respond favorably to either the drug or the placebo. Of the 100 subjects, 51 respond favorably to the drug, while 49 do not. 23 of the 100 subjects respond favorably to the placebo, while 77 do not.

Example 20.2 A researcher conducts a study to investigate whether or not a weekly television series that is highly critical of the use of animals as subjects in medical research influences public opinion. One hundred randomly selected subjects are administered a pretest to determine their attitude concerning the use of animals in medical research. Based on their responses, subjects are categorized as pro-animal research or anti-animal research. Following the pretest, all of the subjects are instructed to watch the television series (which last two months). At the conclusion of the series each subject's attitude toward animal research is reassessed. The results of the study are summarized in Table 20.3. Do the data indicate that a shift in attitude toward animal research occurred after subjects viewed the television series?

Table 20.3 Summary of Data for Example 20.2

		Posttest		Row sums
		Anti	Pro	
Pretest	Anti	10	13	23
	Pro	41	36	77
Column sums		51	49	100

Note that the data in Table 20.3 indicate the following: a) 10 subjects express an anti-animal research attitude on both the pretest and the posttest; b) 13 subjects express an anti-animal research attitude on the pretest but a pro-animal research attitude on the posttest; c) 41 subjects express a pro-animal research attitude on the pretest but an anti-animal research attitude on the posttest; and d) 36 subjects express a pro-animal research attitude on both the pretest and the

posttest. Of the 100 subjects, 23 are anti on the pretest and 77 are pro on the pretest. Of the 100 subjects, 51 are anti on the posttest, while 49 are pro on the posttest.

Table 20.4 summarizes that data for Examples 20.1 and 20.2.

Table 20.4 Summary of Data for Examples 20.1 and 20.2

		Favorable response to drug/Posttest		Row sums
		Yes/Anti	No/Pro	
Favorable response to placebo/Pretest	Yes/Anti	$a = 10$	$b = 13$	23
	No/Pro	$c = 41$	$d = 36$	77
Column sums		51	49	100

III. Null versus Alternative Hypotheses

In conducting the **McNemar test**, the cells of interest in Table 20.4 are Cells b and c , since the latter two cells represent those subjects who respond in different response categories under the two experimental conditions (in the case of a **true experiment**) or in the pretest versus posttest (in the case of a **before–after design**). In Example 20.1, the frequencies recorded in Cells b and c , respectively, represent subjects who respond **favorably to the placebo/unfavorably to the drug** and **favorably to the drug/unfavorably to the placebo**. If the drug is more effective than the placebo, one would expect the proportion of subjects in Cell c to be larger than the proportion of subjects in Cell b . In Example 20.2, the frequencies recorded in Cells b and c , respectively, represent subjects who are **anti-animal research in the pretest/pro-animal research in the posttest** and **pro-animal research in the pretest/anti-animal research in the posttest**. If there is a shift in attitude from the pretest to the posttest (specifically from **pro-animal research** to **anti-animal research**), one would expect the proportion of subjects in Cell c to be larger than the proportion of subjects in Cell b .

It will be assumed that in the underlying population, π_b and π_c represent the following proportions: $\pi_b = b/(b + c)$ and $\pi_c = c/(b + c)$. If there is no difference between the two experimental conditions (in the case of a **true experiment**) or between the pretest and the posttest (in the case of a **before–after design**), the following will be true: $\pi_b = \pi_c = .5$. With respect to the sample data, the values π_b and π_c are estimated with the values p_b and p_c , which in the case of Examples 20.1 and 20.2 are $p_b = b/(b + c) = 13/(13 + 41) = .24$ and $p_c = c/(b + c) = 41/(13 + 41) = .76$.

Employing the above information the null and alternative hypotheses for the **McNemar test** can now be stated.²

Null hypothesis

$$H_0: \pi_b = \pi_c$$

(In the underlying population the sample represents, the proportion of observations in Cell b equals the proportion of observations in Cell c .)

Alternative hypothesis

$$H_1: \pi_b \neq \pi_c$$

(In the underlying population the sample represents, the proportion of observations in Cell b does not equal the proportion of observations in Cell c . This is a **nondirectional alternative hypothesis** and it is evaluated with a two-tailed test. In order to be supported, the proportion of observations in Cell b (p_b) can be either significantly larger or significantly smaller than the proportion of observations in Cell c (p_c). In the case of Example 20.1, this alternative hypothesis

will be supported if the proportion of subjects who respond **favorably to the placebo/unfavorably to the drug** is significantly greater than the proportion of subjects who respond **favorably to the drug/unfavorably to the placebo**, or the proportion of subjects who respond **favorably to the drug/unfavorably to the placebo** is significantly greater than the proportion of subjects who respond **favorably to the placebo/unfavorably to the drug**. In the case of Example 20.2, this alternative hypothesis will be supported if, in the pretest versus posttest, a significantly larger proportion of subjects shift their response from **pro-animal research** to **anti-animal research** or a significantly larger proportion of subjects shift their response from **anti-animal research** to **pro-animal research**.)

or

$$H_1: \pi_b > \pi_c$$

(In the underlying population the sample represents, the proportion of observations in Cell b is greater than the proportion of observations in Cell c . This is a **directional alternative hypothesis** and it is evaluated with a one-tailed test. In order to be supported, the proportion of observations in Cell b (p_b) must be significantly larger than the proportion of observations in Cell c (p_c). In the case of Example 20.1, this alternative hypothesis will be supported if the proportion of subjects who respond **favorably to the placebo/unfavorably to the drug** is significantly greater than the proportion of subjects who respond **favorably to the drug/unfavorably to the placebo**. In the case of Example 20.2, this alternative hypothesis will be supported if, in the pretest versus posttest, a significantly larger proportion of subjects shift their response from **anti-animal research** to **pro-animal research**.)

or

$$H_1: \pi_b < \pi_c$$

(In the underlying population the sample represents, the proportion of observations in Cell b is less than the proportion of observations in Cell c . This is a **directional alternative hypothesis** and it is evaluated with a one-tailed test. In order to be supported, the proportion of observations in Cell b (p_b) must be significantly smaller than the proportion of observations in Cell c (p_c). In the case of Example 20.1, this alternative hypothesis will be supported if the proportion of subjects who respond **favorably to the drug/unfavorably to the placebo** is significantly greater than the proportion of subjects who respond **favorably to the placebo/unfavorably to the drug**. In the case of Example 20.2, this alternative hypothesis will be supported if, in the pretest versus posttest, a significantly larger proportion of subjects shift their responses from **pro-animal research** to **anti-animal research**.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis is rejected.

IV. Test Computations

The test statistic for the **McNemar test**, which is based on the chi-square distribution, is computed with Equation 20.1.³

$$\chi^2 = \frac{(b - c)^2}{b + c} \quad \text{(Equation 20.1)}$$

Where: b and c represent the number of observations in Cells b and c of the **McNemar test** summary table

Substituting the appropriate values in Equation 20.1, the value $\chi^2 = 14.52$ is computed for Examples 20.1/20.2.

$$\chi^2 = \frac{(13 - 41)^2}{13 + 41} = 14.52$$

The computed chi-square value must always be a positive number. If a negative value is obtained, it indicates that an error has been made. The only time the value of chi-square will equal zero is when $b = c$.

V. Interpretation of the Test Results

The obtained value $\chi^2 = 14.52$ is evaluated with **Table A4 (Table of the Chi-Square Distribution)** in the **Appendix**.⁴ The degrees of freedom employed in the analysis are $df = 1$.⁵ Employing **Table A4**, for $df = 1$ the tabled critical two-tailed .05 and .01 chi-square values are $\chi^2_{.05} = 3.84$ (which corresponds to the chi-square value at the 95th percentile) and $\chi^2_{.01} = 6.63$ (which corresponds to the chi-square value at the 99th percentile). The tabled critical one-tailed .05 and .01 values are $\chi^2_{.05} = 2.71$ (which corresponds to the chi-square value at the 90th percentile) and $\chi^2_{.01} = 5.43$ (which corresponds to the chi-square value at the 98th percentile).⁶

The following guidelines are employed in evaluating the null hypothesis for the **McNemar test**.

a) If the nondirectional alternative hypothesis $H_1: \pi_b \neq \pi_c$ is employed, the null hypothesis can be rejected if the obtained chi-square value is equal to or greater than the tabled critical two-tailed value at the prespecified level of significance.

b) If a directional alternative hypothesis is employed, only the directional alternative hypothesis that is consistent with the data can be supported. With respect to the latter alternative hypothesis, the null hypothesis can be rejected if the obtained chi-square value is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

Applying the above guidelines to Examples 20.1/20.2, we can conclude the following.

Since the obtained value $\chi^2 = 14.52$ is greater than the tabled critical two-tailed values $\chi^2_{.05} = 3.84$ and $\chi^2_{.01} = 6.63$, the nondirectional alternative hypothesis $H_1: \pi_b \neq \pi_c$ is supported at both the .05 and .01 levels. Since $\chi^2 = 14.52$ is greater than the tabled critical one-tailed values $\chi^2_{.05} = 2.71$ and $\chi^2_{.01} = 5.43$, the directional alternative hypothesis $H_1: \pi_b < \pi_c$ is supported at both the .05 and .01 levels (since $p_b = .24$ is less than $p_c = .76$).

A summary of the analysis of Examples 20.1 and 20.2 with the **McNemar test** follows:

Example 20.1: It can be concluded that the proportion of subjects who respond favorably to the drug is significantly greater than the proportion of subjects who respond favorably to the placebo.

Example 20.2: It can be concluded that following exposure to the television series, there is a significant change in attitude toward the use of animals as subjects in medical research. The direction of the change is from pro-animal research to anti-animal research. It is important to note, however, that since Example 20.2 is based on a **before–after design**, the researcher is not justified in concluding that the change in attitude is a direct result of subjects watching the television series. This is the case because (as noted in Section VII of the **t test for two dependent samples**) a **before–after design** is an incomplete experimental design. Specifically, in order to be an adequately controlled experimental design, a **before–after design** requires the addition of a control group that is administered the identical pretest and posttest at the same time periods as the group described in Example 20.2. The control group, however, would not be exposed to the television series between the pretest and the posttest. Without inclusion of such a control group, it is not possible to determine whether an observed change in attitude from the pretest to

the posttest is due to the experimental treatment (i.e., the television series), or is the result of one or more extraneous variables that may also have been present during the intervening time period between the pretest and the posttest.

VI. Additional Analytical Procedures for the McNemar Test and/or Related Tests

1. Alternative equation for the McNemar test statistic based on the normal distribution
Equation 20.2 is an alternative equation that can be employed to compute the **McNemar test** statistic. It yields a result that is equivalent to that obtained with Equation 20.1.

$$z = \frac{b - c}{\sqrt{b + c}} \quad (\text{Equation 20.2})$$

The sign of the computed z value is only relevant insofar as it indicates the directional alternative hypothesis with which the data are consistent. Specifically, the z value computed with Equation 20.2 will be a positive number if the number of observations in Cell b is greater than the number of observations in Cell c , and it will be a negative number if the number of observations in Cell c is greater than the number of observations in Cell b . Since in Examples 20.1/20.2 $c > b$, the computed value of z will be a negative number. Substituting the appropriate values in Equation 20.2, the value $z = -3.81$ is computed.

$$z = \frac{13 - 41}{\sqrt{13 + 41}} = -3.81$$

The square of the z value obtained with Equation 20.2 will always equal the chi-square value computed with Equation 20.1. This relationship can be confirmed by the fact that $(z = -3.81)^2 = (\chi^2 = 14.52)$. It is also the case that the square of a tabled critical z value at a given level of significance will equal the tabled critical chi-square value at the corresponding level of significance.

The obtained z value is evaluated with **Table A1 (Table of the Normal Distribution)** in the **Appendix**. In **Table A1** the tabled critical two-tailed .05 and .01 values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed .05 and .01 values are $z_{.05} = 1.65$ and $z_{.01} = 2.33$. In interpreting the z value computed with Equation 20.2, the following guidelines are employed.

a) If the nondirectional alternative hypothesis $H_1: \pi_b \neq \pi_c$ is employed, the null hypothesis can be rejected if the obtained absolute value of z is equal to or greater than the tabled critical two-tailed value at the prespecified level of significance.

b) If a directional alternative hypothesis is employed, only the directional alternative hypothesis that is consistent with the data can be supported. With respect to the latter alternative hypothesis, the null hypothesis can be rejected if the obtained absolute value of z is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

Employing the above guidelines with Examples 20.1/20.2, we can conclude the following.

Since the obtained absolute value $z = 3.81$ is greater than the tabled critical two-tailed values $z_{.05} = 1.96$ and $z_{.01} = 2.58$, the nondirectional alternative hypothesis $H_1: \pi_b \neq \pi_c$ is supported at both the .05 and .01 levels. Since the obtained absolute value $z = 3.81$ is greater than the tabled critical one-tailed values $z_{.05} = 1.65$ and $z_{.01} = 2.33$, the directional alternative hypothesis $H_1: \pi_b < \pi_c$ is supported at both the .05 and .01 levels. These conclusions are identical to those reached when Equation 20.1 is employed to evaluate the same set of data.

2. The correction for continuity for the McNemar test Since the **McNemar test** employs a continuous distribution to approximate a discrete probability distribution, some sources recommend that a correction for continuity be employed in computing the test statistic. Sources that recommend such a correction, either recommend it be limited to small sample sizes or that it be used in all instances.⁷ Equations 20.3 and 20.4 are the continuity-corrected versions of Equations 20.1 and 20.2.⁸

$$\chi^2 = \frac{(|b - c| - 1)^2}{b + c} \quad (\text{Equation 20.3})$$

$$z = \frac{|b - c| - 1}{\sqrt{b + c}} \quad (\text{Equation 20.4})$$

Substituting the appropriate values in Equations 20.3 and 20.4, the values $\chi^2 = 13.5$ and $z = 3.67$ are computed for Examples 20.1/20.2.

$$\chi^2 = \frac{(|13 - 41| - 1)^2}{13 + 41} = 13.5$$

$$z = \frac{|13 - 41| - 1}{\sqrt{13 + 41}} = 3.67$$

As is the case without the continuity correction, the square of the z value obtained with Equation 20.4 will always equal the chi-square value computed with Equation 20.3. This relationship can be confirmed by the fact that $(z = 3.67)^2 = (\chi^2 = 13.5)$. Note that the chi-square value computed with Equation 20.3 will always be less than the value computed with Equation 20.1. In the same respect, the absolute value of z computed with Equation 20.4 will always be less than the absolute value of z computed with Equation 20.2. The lower absolute values computed for the continuity-corrected statistics reflect the fact that the latter analysis provides a more conservative test of the null hypothesis than does the uncorrected analysis. In this instance, the decision the researcher makes with respect to the null hypothesis is not affected by the correction for continuity, since the values $\chi^2 = 13.5$ and $z = 3.67$ are both greater than the relevant tabled critical one- and two-tailed .05 and .01 values. Thus, the nondirectional alternative hypothesis $H_1: \pi_b \neq \pi_c$ and the directional alternative hypothesis $H_1: \pi_b < \pi_c$ are supported at both the .05 and .01 levels.

3. Computation of the exact binomial probability for the McNemar test model with a small sample size In Section I it is noted that the exact probability distribution for the **McNemar test** model is the binomial distribution, and that the chi-square distribution is employed to approximate the latter distribution. Although for large sample sizes the chi-square distribution provides an excellent approximation of the binomial distribution, many sources recommend that for small sample sizes the exact binomial probabilities be computed. In order to demonstrate the computation of an exact binomial probability for the **McNemar test** model, assume that [Table 20.5](#) is a revised summary table for Examples 20.1/20.2.

Note that although the frequencies for Cells a and d in [Table 20.5](#) are identical to those employed in [Table 20.4](#), different frequencies are employed for Cells b and c . Although in [Table 20.5](#) the total sample size of $n = 56$ is reasonably large, the total number of subjects in Cells b and c is quite small, and, in the final analysis, it is when the sum of the frequencies of the latter two cells is small that computation of the exact binomial probability is recommended. The fact that the frequencies of Cells a and d are not taken into account represents an obvious

Table 20.5 Revised Summary Table for Examples 20.1 and 20.2 for Binomial Analysis

		Favorable response to drug/Posttest		
		Yes/Anti	No/Pro	Row sums
Favorable response to placebo/Pretest	Yes/Anti	$a = 10$	$b = 2$	12
	No/Pro	$c = 8$	$d = 36$	44
Column sums		18	38	56

limitation of the **McNemar test**. In point of fact, the frequencies of Cells a and d could be 0 and 0 instead of 10 and 36, and the same result will be obtained when the **McNemar test** statistic is computed. In the same respect, frequencies of 1000 and 3600 for Cells a and d will also yield the identical result. Common sense suggests, however, that the difference $|b - c| = |2 - 8| = 6$ will be considered more important if the total sample size is small (which will be the case if the frequencies of Cells a and d are 0 and 0) than if the total sample size is very large (which will be the case if the frequencies of Cells a and d are 1000 and 3600). What the latter translates into is that a significant difference between Cells b and c may be of little or no practical significance, if the total number of observations in all four cells is very large.

Employing Equations 20.1 and 20.2 with the data in [Table 20.5](#), the values $\chi^2 = 3.6$ and $z = 1.90$ are computed for the **McNemar test** statistic.

$$\chi^2 = \frac{(2 - 8)^2}{2 + 8} = 3.6$$

$$z = \frac{2 - 8}{\sqrt{2 + 8}} = 1.90$$

Employing Equations 20.3 and 20.4, the values $\chi^2 = 2.5$ and $z = 1.58$ are the continuity-corrected values computed for the **McNemar test** statistic.

$$\chi^2 = \frac{(|2 - 8| - 1)^2}{2 + 8} = 2.5$$

$$z = \frac{|2 - 8| - 1}{\sqrt{2 + 8}} = 1.58$$

Employing [Table A1](#), we determine that the exact one-tailed probability for the value $z = 1.90$ computed with Equation 20.2 (as well as for $\chi^2 = 3.6$ computed with Equation 20.1) is .0287. We also determine that the exact one-tailed probability for the value $z = 1.58$ computed with Equation 20.4 (as well as for $\chi^2 = 2.5$ computed with Equation 20.3) is .0571.⁹ Note that since the continuity-correction results in a more conservative test, the probability associated with the continuity corrected value will always be higher than the probability associated with the uncorrected value. Without the continuity correction, the directional alternative hypothesis $H_1: \pi_b < \pi_c$ is supported at the .05 level, since $\chi^2 = 3.6/z = 1.90$ are greater than the tabled critical one-tailed values $\chi^2_{.05} = 2.71/z_{.05} = 1.65$. The nondirectional alternative hypothesis $H_1: \pi_b \neq \pi_c$ is not supported, since $\chi^2 = 3.6/z = 1.90$ are less than the tabled critical two-tailed values $\chi^2_{.05} = 3.84/z_{.05} = 1.96$. When the continuity correction is employed, the directional alternative hypothesis $H_1: \pi_b < \pi_c$ fails to achieve significance at the .05 level, since $\chi^2 = 2.5/z = 1.58$ are less than $\chi^2_{.05} = 2.71/z_{.05} = 1.65$. The nondirectional

alternative hypothesis $H_1: \pi_b \neq \pi_c$ is not supported, since $\chi^2 = 2.5/z = 1.58$ are less than the tabled critical two-tailed values $\chi_{.05}^2 = 3.84/z_{.05} = 1.96$.

At this point, the exact binomial probability will be computed for the same set of data. As is the case with the equations for the **McNemar test** that are based on the chi-square and normal distributions, the binomial analysis only considers the frequencies of Cells b and c . Since only two cells are taken into account, the binomial analysis becomes identical to the analysis described for the **binomial sign test for a single sample (Test 9)**.¹⁰

Equation 20.5 is the binomial equation that is employed to determine the likelihood of obtaining a frequency of 8 or larger in one of the two cells (or 2 or less in one of the two cells) in the McNemar model summary table, if the total frequency in the two cells is 10, where, $m = b + c = 2 + 8 = 10$. Note that Equation 20.5 is identical to Equation 9.5, except for the fact that π_b and π_c are used in place of π_1 and π_2 , and the value m , which represents $b + c$, is used in place of n .

$$P(\geq x) = \sum_{r=x}^m \binom{m}{r} (\pi_b)^r (\pi_c)^{(m-r)} \quad \text{(Equation 20.5)}$$

In evaluating the data in [Table 20.5](#), the following values are employed in Equation 20.5: $\pi_b = \pi_c = .5$ (which will be the case if the null hypothesis is true), $m = 10$, $x = 8$.

$$P(x \geq 8) = \binom{10}{8} (.5)^8 (.5)^2 + \binom{10}{9} (.5)^9 (.5)^1 + \binom{10}{10} (.5)^{10} (.5)^0 = .0547$$

The computed probability .0547 is the likelihood of obtaining a frequency of 8 or greater in one of the two cells (as well as the likelihood of obtaining a frequency of 2 or less in one of the two cells). The value .0547 can also be obtained from [Table A7 \(Table of the Binomial Distribution, Cumulative Probabilities\)](#) in the **Appendix**. In using [Table A7](#) we find the section for $m = 10$ (which is represented by $n = 10$ in the table), and locate the cell that is the intersection of the row $x = 8$ and the column $\pi = .5$. The entry for the latter cell is .0547. The value .0547 computed for the exact binomial probability is quite close to the continuity-corrected probability of .0571 obtained with Equations 20.3/20.4 (which suggests that even when the sample size is small, the continuity-corrected chi-square/normal approximation provides an excellent estimate of the exact probability). As is the case when the data are evaluated with Equations 20.3/20.4, the directional alternative hypothesis $H_1: \pi_b < \pi_c$ is not supported if the binomial analysis is employed. This is the case, since the probability .0547 is greater than $\alpha = .05$. In order for the directional alternative hypothesis $H_1: \pi_b < \pi_c$ to be supported, the tabled probability must be equal to or less than $\alpha = .05$. The nondirectional alternative hypothesis $H_1: \pi_b \neq \pi_c$ is also not supported, since the probability .0547 is greater than $\alpha/2 = .05/2 = .025$.¹¹

4. Additional analytical procedures for the McNemar test

a) A procedure for computing a confidence interval for the difference between the marginal probabilities (i.e., $[(a + b)/n] - [(a + c)/n]$) in a **McNemar test** summary table is described in Marascuilo and McSweeney (1977) and Fleiss (1981).

b) Daniel (1990) and Fleiss (1981) provide references that discuss the power of the **McNemar test** relative to alternative procedures (such as the **Gart test for order effects** which is discussed in Section VII). Zar (1999, p. 171) describes power computations for the **McNemar test**.

b) Fleiss (1981), who provides a detailed discussion of the **McNemar test**, notes that an **odds ratio** (which is discussed in Section VI of the **chi-square test for $r \times c$ tables (Test 16)**)

can be computed for the **McNemar test** summary table. Specifically, the **odds ratio** (o) is computed with Equation 20.6. Employing the latter equation, the value $o = 3.15$ is computed for Example 20.1.

$$o = \frac{c}{b} = \frac{41}{13} = 3.15 \quad (\text{Equation 20.6})$$

In reference to Example 20.1, the computed value $o = 3.15$ indicates that the odds of a person responding to the drug are 3.15 times greater than the odds of a person responding to the placebo.

c) Fleiss (1981) also notes that if the null hypothesis is rejected in a study such as that described by Example 20.1, Equation 20.7 can be employed to determine the relative difference (represented by the notation p_e) between the two treatments. Equation 20.7 is employed with the data for Example 20.1 to compute the value $p_e = .36$.

$$p_e = \frac{c - b}{c + d} = \frac{41 - 13}{41 + 36} = .36 \quad (\text{Equation 20.7})$$

The computed value .36 indicates that in a sample of 100 patients who do not respond favorably to the placebo, $(.36)(100) = 36$ would be expected to respond favorably to the drug. Fleiss (1981) describes the computation of the estimated standard error for the value of the relative difference computed with Equation 20.7, as well as the procedure for computing a confidence interval for the relative difference.

d) In Section IX (the **Addendum**) of the **Pearson product-moment correlation coefficient (Test 28)**, the use of the **phi coefficient (Test 16g)** described in Section VI of the **chi-square test for $r \times c$ tables** as a measure of association for the **McNemar test** model is discussed within the context of the **tetrachoric correlation coefficient (Test 28j)**.

VII. Additional Discussion of the McNemar Test

1. Alternative format for the McNemar test summary table and modified test equation

Although in this book Cells b and c are designated as the two cells in which subjects are inconsistent with respect to their response categories, the **McNemar test** summary table can be rearranged so that Cells a and d become the relevant cells. Table 20.6 represents such a rearrangement with respect to the response categories employed in Examples 20.1/20.2.

Table 20.6 Alternative Format for Summary of Data for Examples 20.1 and 20.2

		Favorable response to drug/Posttest		Row sums
		Yes/Anti	No/Pro	
Favorable response to placebo/Pretest	No/Pro	$a = 41$	$b = 36$	77
	Yes/Anti	$c = 10$	$d = 13$	23
Column sums		51	49	100

Note that in Table 20.6 Cells a and d are the key cells, since subjects who are inconsistent with respect to response categories are represented in these two cells. If Table 20.6 is employed as the summary table for the **McNemar test**, Cells a and d will, respectively, replace Cells c and b in stating the null and alternative hypotheses. In addition, Equations 20.8 and 20.9 will, re-

spectively, be employed in place of Equations 20.1 and 20.2. When the appropriate values are substituted in the aforementioned equations, Equation 20.8 yields the value $\chi^2 = 14.52$ computed with Equation 20.1, and Equation 20.9 yields the value $z = -3.81$ computed with Equation 20.2.

$$\chi^2 = \frac{(d - a)^2}{d + a} = \frac{(13 - 41)^2}{13 + 41} = 14.52 \quad (\text{Equation 20.8})$$

$$z = \frac{d - a}{\sqrt{d + a}} - \frac{13 - 41}{\sqrt{13 + 41}} = -3.81 \quad (\text{Equation 20.9})$$

2. Alternative nonparametric procedures for evaluating a design with two dependent samples involving categorical data Gart (1969) has developed a test for evaluating a design with two dependent samples involving categorical data that can determine whether the order of presentation of two treatments influences subjects' responses to the treatments. The **Gart test for order effects** is based on the use of the **Fisher exact test (Test 16c)** with two 2×2 contingency tables, which summarize the responses of subjects in relation to the differential treatments as well as the order of presentation of the treatments. The **Gart test for order effects** is described in Everitt (1977, pp. 22–26; 1992) and Zar (1999, pp. 173–175). The **McNemar test** model has been extended by Bowker (1948) (**The Bowker test of symmetry (Test 20a)**) and Stuart (1955, 1957) (**The Stuart test**) to a dependent samples design in which the dependent variable is a categorical measure that is comprised of more than two categories. The latter two tests are discussed in Section IX (the **Addendum**).

VIII. Additional Examples Illustrating the Use of the McNemar Test

Three additional examples that can be evaluated with the **McNemar test** are presented in this section. Since Examples 20.3–20.5 employ the same data employed in Example 20.1, they yield the identical result.

Example 20.3 *In order to determine if there is a relationship between schizophrenia and enlarged cerebral ventricles, a researcher evaluates 100 pairs of identical twins who are discordant with respect to schizophrenia (i.e., within each twin pair, only one member of the pair has schizophrenia). Each subject is evaluated with a CAT scan to determine whether or not there is enlargement of the ventricles. The results of the study are summarized in Table 20.7. Do the data indicate there is a statistical relationship between schizophrenia and enlarged ventricles?*

Table 20.7 Summary of Data for Example 20.3

		Schizophrenic twin		Row sums
		Enlarged ventricles	Normal ventricles	
Normal twin	Enlarged ventricles	10	13	23
	Normal ventricles	41	36	77
Column sums		51	49	100

Since Table 20.7 summarizes categorical data derived from $n = 100$ pairs of matched subjects, the **McNemar test** is employed to evaluate the data. The reader should take note of the fact that since the independent variable employed in Example 20.3 is **nonmanipulated** (specifically, it is whether or not a subject is **schizophrenic** or **normal**), analysis of the data will only provide correlational information, and thus will not allow the researcher to draw conclusions with

regard to cause and effect. In other words, although the study indicates that schizophrenic subjects are significantly more likely than normal subjects to have enlarged ventricles, one cannot conclude that enlarged ventricles cause schizophrenia or that schizophrenia causes enlarged ventricles. Although either of the latter is possible, the design of the study only allows one to conclude that the presence of enlarged ventricles is associated with schizophrenia.

Example 20.4 *A company that manufactures an insecticide receives complaints from its employees about premature hair loss. An air quality analysis reveals a large concentration of a vaporous compound emitted by the insecticide within the confines of the factory. In order to determine whether or not the vaporous compound (which is known as Acherton) is related to hair loss, the following study is conducted. Each of 100 mice is exposed to air containing high concentrations of Acherton over a two-month period. The same mice are also exposed to air that is uncontaminated with Acherton during another two-month period. Half of the mice are initially exposed to the Acherton contaminated air followed by the uncontaminated air, while the other half are initially exposed to the uncontaminated air followed by the Acherton contaminated air. The dependent variable in the study is whether or not a mouse exhibits hair loss during an experimental condition. Table 20.8 summarizes the results of the study. Do the data indicate a relationship between Acherton and hair loss?*

Table 20.8 Summary of Data for Example 20.4

		Acherton contaminated air		Row sums
		Hair loss	No hair loss	
Uncontaminated air	Hair loss	10	13	23
	No hair loss	41	36	77
	Column sums	51	49	100

Analysis of the data in Table 20.8 reveals that the mice are significantly more likely to exhibit hair loss when exposed to Acherton as opposed to when they are exposed to uncontaminated air. Although the results of the study suggest that Acherton may be responsible for hair loss, one cannot assume that the results can be generalized to humans.

Example 20.5 *A market research firm is hired to determine whether or not a debate between the two candidates who are running for the office of Governor influences voter preference. The gubernatorial preference of 100 randomly selected voters is determined before and after a debate between the two candidates, Edgar Vega and Vera Myers. Table 20.9 summarizes the results of the voter preference survey. Do the data indicate that the debate influenced voter preference?*

Table 20.9 Summary of Data for Example 20.5

		Voter preference before debate		Row sums
		Edgar Vega	Vera Meyers	
Voter preference after debate	Edgar Vega	10	13	23
	Vera Meyers	41	36	77
	Column sums	51	49	100

When the data for Example 20.5 (which represents a **before-after design**) are evaluated

with the **McNemar test**, the result indicates that, following the debate, there is a significant shift in voter preference in favor of Vera Myers. As noted in Section V, since a **before-after design** does not adequately control for the potential influence of extraneous variables, one cannot rule out the possibility that some factor other than the debate is responsible for the shift in voter preference.

IX. Addendum

Extension of the McNemar test model beyond 2×2 contingency tables The **McNemar test** model has been extended by Bowker (1948) and Stuart (1955, 1957) to a dependent samples design in which the dependent variable is a categorical measure that is comprised of more than two categories. In the test models for the **Bowker test of symmetry (Test 20a)** (which will be described in this section), and the **Stuart test**, a $k \times k$ (i.e., square) contingency table (where k is the number of response categories, and $k \geq 3$) is employed to categorize n subjects (or n pairs of matched subjects) on a dependent variable under the two conditions (or two time periods).¹² The **Bowker test** evaluates differences with respect to the joint probability distributions, or to put it more simply, whether the data are distributed symmetrically about the main diagonal of the table. The **Stuart test**, on the other hand, evaluates differences between marginal probabilities.

Test 20a: The Bowker test of symmetry Bowker (1948) has developed a test to evaluate whether or not the data in a $k \times k$ contingency table are distributed symmetrically about the main diagonal of the table. Note that in a $k \times k$ contingency table, $k = r = c$ (i.e., the numbers of rows and columns are equal). A lack of symmetry in a $k \times k$ table is interpreted to mean that there is a difference in the distribution of the data under the two experimental conditions/time periods. In the case of a 2×2 table, the **Bowker test** becomes equivalent to the **McNemar test**. Example 20.6 will be employed to illustrate the use of the **Bowker test of symmetry**.

Example 20.6 *Two drugs that are believed to have mood-altering effects are tested on 275 subjects. The order of administration of the drugs is counterbalanced so that half the subjects receive Drug A followed by Drug B, while the reverse sequence of administration is used for the other subjects. Based on his response to each drug a subject is assigned to one of the following three response categories: No change in mood (NC); Moderate mood alteration (MA); Dramatic mood alteration (DA). Table 20.10 represents a joint distribution that summarizes the responses of the 275 subjects to both of the drugs. (The value in any cell in Table 20.10 represents the number of subjects whose response to Drug A corresponds to the column category for that cell, and whose response to Drug B corresponds to the row category for that cell.) Do the data indicate that the two drugs differ with respect to their mood- altering properties?*

Table 20.10 Summary of Data for Example 20.6

		Response to Drug A			Row sums
		NC	MA	DA	
Response to Drug B	NC	25	10	16	51
	MA	20	50	14	84
	DA	30	40	70	140
Column sums		75	100	100	275

The null and alternative hypotheses evaluated with the **Bowker test of symmetry** are as

follows.

Null hypothesis $H_0: p_{ij} = p_{ji}$ (where $j > i$)

(In the $k \times k$ contingency table, the probabilities are equal for each of the off-diagonal/symmetric pairs. The latter translates into the fact that the distribution of data above the main diagonal of the $k \times k$ contingency table is the same as the distribution of data below the main diagonal. With respect to Example 20.6, the null hypothesis is stating that the response distributions of subjects for the two drugs will be the same.)

Alternative hypothesis $H_1: p_{ij} \neq p_{ji}$ for at least one cell (where $j > i$)

(In the $k \times k$ contingency table, the probabilities are not equal for at least one pair of the total off-diagonal/symmetric pairs. The latter translates into the fact that the distribution of data above the main diagonal of the $k \times k$ contingency table is not the same as the distribution of data below the main diagonal. With respect to Example 20.6, the null hypothesis is stating that the response distributions of subjects for the two drugs will not be the same. The alternative hypothesis is **nondirectional**.)¹³

Equation 20.10 is employed to compute the test statistic for the **Bowker test of symmetry**.

$$\chi^2 = \sum_{i=1}^r \sum_{j>i} \left[\frac{(n_{ij} - n_{ji})^2}{n_{ij} + n_{ji}} \right] \quad \text{(Equation 20.10)}$$

The notation in Equation 20.10 indicates the following: a) Each frequency above the main diagonal that is in Row i and Column j (i.e., n_{ij} , where $j > i$) is paired with the frequency below the main diagonal that is in Row j and Column i (i.e., n_{ji} , where $j < i$). The latter pair is referred to as an **off-diagonal** or **symmetric pair**. Within each of the off-diagonal pairs the following is done: a) The difference between n_{ij} and n_{ji} is obtained; b) The difference is squared; c) The squared difference is divided by the sum of n_{ij} and n_{ji} ; and d) All of the values computed in part c) are summed, and the resulting value represents the test statistic, which is a chi-square value.

The number of off-diagonal pairs in a table will be equal to $\binom{k}{2}$, which is the number of combinations of k things taken two at a time (see Section IV of the **binomial sign test for a single sample** for a clarification of **combinations**). The number of off-diagonal pairs is also equal to the value $(k \times k - k)/2$, which is equal to $[k(k - 1)]/2$ (which is the number of degrees of freedom employed for the analysis). Thus, if $k = 3$ (i.e., $r = c = 3$), there will be three pairs, since $\binom{3}{2} = 3$, or $(3 \times 3 - 3)/2 = [3(3 - 1)]/2 = 3$. Specifically, the three pairs will involve the following combinations of cell subscripts: 1,2; 1,3; and 2, 3. Thus, the following pairs of cells will be contrasted through use of Equation 20.10 (where the first digit represents the row (i) in which the cell appears, and the second digit represents the column (j) in which the cell appears): Cell₁₂ versus Cell₂₁; Cell₁₃ versus Cell₃₁, Cell₂₃ versus Cell₃₂. Note that for the first cell listed in each pair, $j > i$, and for the second cell in each pair, $j < i$.

The data for Example 20.6 are evaluated below with Equation 20.10.

$$\begin{aligned} \chi^2 &= \frac{(n_{12} - n_{21})^2}{(n_{12} + n_{21})} + \frac{(n_{13} - n_{31})^2}{(n_{13} + n_{31})} + \frac{(n_{23} - n_{32})^2}{(n_{23} + n_{32})} \\ \chi^2 &= \frac{(10 - 20)^2}{(10 + 20)} + \frac{(16 - 30)^2}{(16 + 30)} + \frac{(14 - 40)^2}{(14 + 40)} = 20.11 \end{aligned}$$

As noted earlier, the degrees of freedom employed for the **Bowker test** analysis are $[k(k - 1)]/2$. Since $k = 3$, $df = [3(3-1)]/2 = 3$. Employing **Table A4**, the tabled critical .05 and .01 chi-square values for $df = 3$ are $\chi^2_{.05} = 7.81$ and $\chi^2_{.01} = 11.34$. In order to reject the null hypothesis, the computed value of chi-square must be equal to or greater than the tabled critical value at the prespecified level of significance. Since the computed value $\chi^2 = 20.11$ is greater than both of the aforementioned critical values, the null hypothesis can be rejected at both the .05 and .01 levels. Inspection of **Table 20.6** clearly suggests that Drug B is more likely to be associated with a change in mood than Drug A.

Further discussion of the **Bowker test of symmetry** can be found in Everitt (1977, pp. 114–115; 1992), Marascuilo and McSweeney (1977), Marascuilo and Serlin (1988), Sprent (1993) and Zar (1999).

Everitt (1977, 1992) notes that if on the basis of the **Bowker test** the hypothesis of symmetry (which will generally be the hypothesis of primary interest) is rejected, a researcher may employ the **Stuart test** to further clarify the distribution of the data. The **Stuart test** evaluates the following null hypothesis: $H_0: p_{i.} = p_{.j}$. The latter indicates that all of the corresponding symmetric marginal probabilities are equal (i.e., the probability for the i^{th} row will be equal to the probability for the j^{th} column, with the requirement that $i = j$). Sources that describe the **Stuart test** are Everitt (1977, pp. 115–116; 1992), Fleiss (1981), Hinkle *et al.* (1998), Marascuilo and McSweeney (1977), and Marascuilo and Serlin (1988).

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Endnotes

1. The distinction between a **true experiment** and a **natural experiment** is discussed in more detail in the **Introduction** of the book.
2.
 - a) The reader should take note of the following with respect to the null and alternative hypotheses stated in this section:
 - a) If n represents the total number of observations in Cells a , b , c , and d , the proportion of observations in Cells b and c can also be expressed as follows: b/n and c/n . The latter two values, however, are not equivalent to the values p_b and p_c that are used to estimate the values π_b and π_c employed in the null and alternative hypotheses.
 - b) Many sources employ an alternative but equivalent way of stating the null and alternative hypotheses for the **McNemar test**. Assume that π_1 represents the proportion of observations in the underlying population who respond in Response category 1 in Condition 1/Pretest, and π_2 represents the proportion of observations in the underlying population who respond in Response category 1 in Condition 2/Posttest. With respect to the sample data, the values p_1 and p_2 are employed to estimate π_1 and π_2 , where $p_1 = (a + b)/n$ and $p_2 = (a + c)/n$. In the case of Examples 20.1 and 20.2, $p_1 = (10 + 13)/100 = .23$ and $p_2 = (10 + 41)/100 = .51$. If there is no difference in the proportion of observations in Response category 1 in Condition 1/Pretest versus the proportion of observations in Response category 1 in Condition 2/Posttest, p_1 and p_2 would be expected to be equal, and if the latter is true one can conclude that in the underlying population $\pi_1 = \pi_2$. If, however, $p_1 \neq p_2$ (and consequently in the underlying population $\pi_1 \neq \pi_2$), it indicates a difference between the two experimental conditions in the case of a **true experiment**, and a difference between the pretest and the posttest responses of subjects in the case of a **before–after design**. Employing this information, the null hypothesis can be stated as follows: $H_0: \pi_1 = \pi_2$. The null hypothesis $H_0: \pi_1 = \pi_2$ is equivalent to the null hypothesis $H_0: \pi_b = \pi_c$. The **nondirectional alternative hypothesis** can be stated as $H_1: \pi_1 \neq \pi_2$. The nondirectional alternative hypothesis $H_1: \pi_1 \neq \pi_2$ is equivalent to the nondirectional alternative hypothesis $H_1: \pi_b \neq \pi_c$. The two **directional alternative hypotheses** that can be employed are $H_1: \pi_1 > \pi_2$ or $H_1: \pi_1 < \pi_2$. The directional alternative hypothesis $H_1: \pi_1 > \pi_2$ is equivalent to the directional alternative hypothesis $H_1: \pi_b > \pi_c$. The directional alternative hypothesis $H_1: \pi_1 < \pi_2$ is equivalent to the directional alternative hypothesis $H_1: \pi_b < \pi_c$.
3. It can be demonstrated algebraically that Equation 20.1 is equivalent to Equation 8.2 (which is the equation for the **chi-square goodness-of-fit test (Test 8)**). Specifically, if Cells a and d are eliminated from the analysis, and the **chi-square goodness-of-fit test** is employed to evaluate the observations in Cells b and c , $n = b + c$. If the expected probability for each of the cells is .5, Equation 8.2 reduces to Equation 20.1. As will be noted in Section VI, a limitation of the **McNemar test** (which is apparent from inspection of Equation 20.1) is that it only employs the data for two of the four cells in the contingency table.

4. A general overview of the chi-square distribution and interpretation of the values listed in **Table A4** can be found in Sections I and V of the **single-sample chi-square test for a population variance (Test 3)**.
5. The degrees of freedom are based on Equation 8.3, which is employed to compute the degrees of freedom for the **chi-square goodness-of-fit test**. In the case of the **McNemar test**, $df = k - 1 = 2 - 1 = 1$, since only the observations in Cells *b* and *c* (i.e., $k = 2$ cells) are evaluated.
6. A full discussion of the protocol for determining one-tailed chi-square values can be found in Section VII of the **chi-square goodness-of-fit test**.
7. A general discussion of the correction for continuity can be found under the **Wilcoxon signed-ranks test (Test 6)**. Fleiss (1981) notes that the correction for continuity for the **McNemar test** was recommended by Edwards (1948).
8. The numerator of Equation 20.4 is sometimes written as $(b - c) \pm 1$. In using the latter format, 1 is added to the numerator if the term $(b - c)$ results in a negative value, and 1 is subtracted from the numerator if the term $(b - c)$ results in a positive value. Since we are only interested in the absolute value of z , it is simpler to employ the numerator in Equation 20.4, which results in the same absolute value that is obtained when the alternative form of the numerator is employed. If the alternative form of the numerator is employed for Examples 20.1/20.2, it yields the value $z = -3.67$.
9. The values .0287 and .0571, respectively, represent the proportion of the normal distribution that falls above the values $z = 1.90$ and $z = 1.58$.
10. In point of fact, it can also be viewed as identical to the analysis conducted with the **binomial sign test for two dependent samples**. In Section VII of the **Cochran *Q* test**, it is demonstrated that when the **McNemar test** (as well as the **Cochran *Q* test** when $k = 2$) and the **binomial sign test for two dependent samples** are employed to evaluate the same set of data, they yield equivalent results.
11. For a comprehensive discussion on the computation of binomial probabilities and the use of **Table A7**, the reader should review Section IV of the **binomial sign test for a single sample**.
12. In some sources the **Stuart test** is referred to as the **Stuart–Maxwell test** based on the contribution of Maxwell (1970).
13. Marascuilo and McSweeney (1977) note that it is only possible to state the alternative hypothesis directionally when the number of degrees of freedom employed for the test is 1, which will always be the case for a 2×2 table.

Inferential Statistical Tests Employed with Two or More Independent Samples (and Related Measures of Association/Correlation)

Test 21: **The Single-Factor Between-Subjects
Analysis of Variance**

Test 22: **The Kruskal–Wallis One-Way Analysis
of Variance by Ranks**

Test 23: **The van der Waerden Normal-Scores Test
for k Independent Samples**

Test 21

The Single-Factor Between-Subjects Analysis of Variance (Parametric Test Employed with Interval/Ratio Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test In a set of k independent samples (where $k \geq 2$), do at least two of the samples represent populations with different mean values?

Relevant background information on test The term **analysis of variance** (for which the acronym **ANOVA** is often employed) describes a group of inferential statistical procedures developed by the British statistician Sir Ronald Fisher. Analysis of variance procedures are employed to evaluate whether or not there is a difference between at least two means in a set of data for which two or more means can be computed. The test statistic computed for an analysis of variance is based on the F distribution (which is named after Fisher), which is a continuous theoretical probability distribution. A computed F value (commonly referred to as an **F ratio**) will always fall within the range $0 \leq F \leq \infty$. As is the case with the t and chi-square distributions discussed earlier in the book, there are an infinite number of F distributions — each distribution being a function of the number of degrees of freedom employed in the analysis (with degrees of freedom being a function of both the number of samples and the number of subjects per sample). A more thorough discussion of the F distribution can be found in Section V.

The **single-factor between-subjects analysis of variance** is the most basic of the analysis of variance procedures.¹ It is employed in a hypothesis testing situation involving k independent samples. In contrast to the **t test for two independent samples (Test 11)**, which only allows for a comparison between the means of two independent samples, the **single-factor between-subjects analysis of variance** allows for a comparison of two or more independent samples. The **single-factor between-subjects analysis of variance** is also referred to as the **completely randomized single-factor analysis of variance**, the **simple analysis of variance**, the **one-way analysis of variance**, and the **single-factor analysis of variance**.

In conducting the **single-factor between-subjects analysis of variance**, each of the k sample means is employed to estimate the value of the mean of the population the sample represents. If the computed test statistic is significant, it indicates there is a significant difference between at least two of the sample means in the set of k means. As a result of the latter, the researcher can conclude there is a high likelihood that at least two of the samples represent populations with different mean values.

In order to compute the test statistic for the **single-factor between-subjects analysis of variance**, the **total variability** in the data is divided into **between-groups variability** and **within-groups variability**. **Between-groups variability** (which is also referred to as **treatment variability**) is essentially a measure of the variance of the means of the k samples. **Within-groups variability** (which is essentially an average of the variance within each of the k samples) is variability that is attributable to chance factors that are beyond the control of a researcher.

Since such chance factors are often referred to as experimental error, **within-groups variability** is also referred to as **error** or **residual variability**. The F ratio, which is the test statistic for the **single-factor between-subjects analysis of variance**, is obtained by dividing **between-groups variability** by **within-groups variability**. Since **within-groups variability** is employed as a baseline measure of the variability in a set of data that is beyond a researcher's control, it is assumed that if the k samples are derived from a population with the same mean value, the amount of variability between the sample means (i.e., **between-groups variability**) will be approximately the same value as the amount of variability within any single sample (i.e., **within-groups variability**). If, on the other hand, **between-groups variability** is significantly larger than **within-groups variability** (in which case the value of the F ratio will be larger than 1), it is likely that something in addition to chance factors is contributing to the amount of variability between the sample means. In such a case, it is assumed that whatever it is that differentiates the groups from one another (i.e., the independent variable/experimental treatments) accounts for the fact that **between-groups variability** is larger than **within-groups variability**.² A thorough discussion of the logic underlying the **single-factor between-subjects analysis of variance** can be found in Section VII.

The **single-factor between-subjects analysis of variance** is employed with interval/ratio data and is based on the following assumptions: a) Each sample has been randomly selected from the population it represents; b) The distribution of data in the underlying population from which each of the samples is derived is normal; and c) The third assumption, which is referred to as the **homogeneity of variance** assumption, states that the variances of the k underlying populations represented by the k samples are equal to one another. The homogeneity of variance assumption is discussed in detail in Section VI.³ If any of the aforementioned assumptions of the **single-factor between-subjects analysis of variance** are saliently violated, the reliability of the computed test statistic may be compromised.

II. Example

Example 21.1 *A psychologist conducts a study to determine whether or not noise can inhibit learning. Each of 15 subjects is randomly assigned to one of three groups. Each subject is given 20 minutes to memorize a list of 10 nonsense syllables, which she is told she will be tested on the following day. The five subjects assigned to **Group 1**, the **no noise** condition, study the list of nonsense syllables while they are in a quiet room. The five subjects assigned to **Group 2**, the **moderate noise** condition, study the list of nonsense syllables while listening to classical music. The five subjects assigned to **Group 3**, the **extreme noise** condition, study the list of nonsense syllables while listening to rock music. The number of nonsense syllables correctly recalled by the 15 subjects follows: **Group 1**: 8, 10, 9, 10, 9; **Group 2**: 7, 8, 5, 8, 5; **Group 3**: 4, 8, 7, 5, 7. Do the data indicate that noise influenced subjects' performance?*

III. Null versus Alternative Hypotheses

Null hypothesis

$$H_0: \mu_1 = \mu_2 = \mu_3$$

(The mean of the population Group 1 represents equals the mean of the population Group 2 represents equals the mean of the population Group 3 represents.)

Alternative hypothesis

$$H_1: \text{Not } H_0$$

(This indicates there is a difference between at least two of the $k = 3$ population means. It is important to note that the alternative hypothesis should not be written as follows:

$H_1: \mu_1 \neq \mu_2 \neq \mu_3$. The reason why the latter notation for the alternative hypothesis is incorrect is because it implies that all three population means must differ from one another in order to reject the null hypothesis. In this book it will be assumed (unless stated otherwise) that the alternative hypothesis for the analysis of variance is stated **nondirectionally**.⁴ In order to reject the null hypothesis, the obtained F value must be equal to or greater than the tabled critical F value at the prespecified level of significance.)

IV. Test Computations

The test statistic for the **single-factor between-subjects analysis of variance** can be computed with either **computational** or **definitional equations**. Although definitional equations reveal the underlying logic behind the analysis of variance, they involve considerably more calculations than the computational equations. Because of the latter, computational equations will be employed in this section to demonstrate the computation of the test statistic. The definitional equations for the **single-factor between-subjects analysis of variance** are described in Section VII.

The data for Example 21.1 are summarized in Table 21.1. The scores of the $n_1 = 5$ subjects in Group 1 are listed in the column labelled X_1 , the scores of the $n_2 = 5$ subjects in Group 2 are listed in the column labelled X_2 , and the scores of the $n_3 = 5$ subjects in Group 3 are listed in the column labelled X_3 . Since there are an equal number of subjects in each group, the notation n is employed to represent the number of subjects per group. In other words, $n = n_1 = n_2 = n_3$. The columns labelled X_1^2 , X_2^2 , and X_3^2 list the squares of the scores of the subjects in each of the three groups.

Table 21.1 Data for Example 21.1

Group 1		Group 2		Group 3	
X_1	X_1^2	X_2	X_2^2	X_3	X_3^2
8	64	7	49	4	16
10	100	8	64	8	64
9	81	5	25	7	49
10	100	8	64	5	25
9	81	5	25	7	49
$\Sigma X_1 = 46$	$\Sigma X_1^2 = 426$	$\Sigma X_2 = 33$	$\Sigma X_2^2 = 227$	$\Sigma X_3 = 31$	$\Sigma X_3^2 = 203$
$\bar{X}_1 = \frac{\Sigma X_1}{n_1} = \frac{46}{5} = 9.2$		$\bar{X}_2 = \frac{\Sigma X_2}{n_2} = \frac{33}{5} = 6.6$		$\bar{X}_3 = \frac{\Sigma X_3}{n_3} = \frac{31}{5} = 6.2$	

The notation N represents the total number of subjects employed in the experiment. Thus:

$$N = n_1 + n_2 + \cdots + n_k$$

Since there are $k = 3$ groups:

$$N = n_1 + n_2 + n_3 = 5 + 5 + 5 = 15$$

The value ΣX_T represents the total sum of the scores of the N subjects who participate in the experiment. Thus:

$$\Sigma X_T = \Sigma X_1 + \Sigma X_2 + \cdots + \Sigma X_k$$

Since there are $k = 3$ groups, $\Sigma X_T = 110$.

$$\Sigma X_T = \Sigma X_1 + \Sigma X_2 + \Sigma X_3 = 46 + 33 + 31 = 110$$

\bar{X}_T represents the grand mean, where $\bar{X}_T = \Sigma X_T / N$. Thus, $\bar{X}_T = 110/15 = 7.33$. Although \bar{X}_T is not employed in the computational equations to be described in this section, it is employed in some of the definitional equations described in Section VII.

The value ΣX_T^2 represents the total sum of the squared scores of the N subjects who participate in the experiment. Thus:

$$\Sigma X_T^2 = \Sigma X_1^2 + \Sigma X_2^2 + \dots + \Sigma X_k^2$$

Since there are $k = 3$ groups, $\Sigma X_T^2 = 856$.

$$\Sigma X_T^2 = \Sigma X_1^2 + \Sigma X_2^2 + \Sigma X_3^2 = 426 + 227 + 203 = 856$$

Although the group means are not required for computing the analysis of variance test statistic, it is recommended that they be computed since visual inspection of the group means can provide the researcher with a general idea of whether or not it is reasonable to expect a significant result. To be more specific, if two or more of the group means are far removed from one another, it is likely that the analysis of variance will be significant (especially if the number of subjects in each group is reasonably large). Another reason for computing the group means is that they are required for comparing individual groups with one another, something that is often done following the analysis of variance on the full set of data. The latter types of comparisons are described in Section VI.

As noted in Section I, in order to compute the test statistic for the **single-factor between-subjects analysis of variance**, the **total variability** in the data is divided into **between-groups variability** and **within-groups variability**. In order to do this, the following values are computed: a) The **total sum of squares** which is represented by the notation SS_T ; b) The **between-groups sum of squares** which is represented by the notation SS_{BG} . The **between-groups sum of squares** is the numerator of the equation that represents **between-groups variability** (i.e., the equation that represents the amount of variability between the means of the k groups); and c) The **within-groups sum of squares** which is represented by the notation SS_{WG} . The **within-groups sum of squares** is the numerator of the equation that represents **within-groups variability** (i.e., the equation that represents the average amount of variability within each of the k groups, which, as noted earlier, represents error variability).

Equation 21.1 describes the relationship between SS_T , SS_{BG} , and SS_{WG} .

$$SS_T = SS_{BG} + SS_{WG} \quad (\text{Equation 21.1})$$

Equation 21.2 is employed to compute SS_T .

$$SS_T = \Sigma X_T^2 - \frac{(\Sigma X_T)^2}{N} \quad (\text{Equation 21.2})$$

Employing Equation 21.2, the value $SS_T = 49.33$ is computed.

$$SS_T = 856 - \frac{(110)^2}{15} = 49.33$$

Equation 21.3 is employed to compute SS_{BG} . In Equation 21.3, the notation n_j and ΣX_j , respectively, represent the values of n and ΣX for the j^{th} group/sample.

$$SS_{BG} = \sum_{j=1}^k \left[\frac{(\Sigma X_j)^2}{n_j} \right] - \frac{(\Sigma X_T)^2}{N} \quad (\text{Equation 21.3})$$

The notation $\sum_{j=1}^k [(\Sigma X_j)^2/n_j]$ in Equation 21.3 indicates that for each group the value $(\Sigma X_j)^2/n_j$ is computed, and the latter values are summed for all k groups. When there are an equal number of subjects in each group (as is the case in Example 21.1), the notation n can be employed in Equation 21.3 in place of n_j .⁵

With reference to Example 21.1, Equation 21.3 can be rewritten as follows:

$$SS_{BG} = \left[\frac{(\Sigma X_1)^2}{n_1} + \frac{(\Sigma X_2)^2}{n_2} + \frac{(\Sigma X_3)^2}{n_3} \right] - \frac{(\Sigma X_T)^2}{N}$$

Substituting the appropriate values from Example 21.1 in Equation 21.3, the value $SS_{BG} = 26.53$ is computed.⁶

$$SS_{BG} = \left[\frac{(46)^2}{5} + \frac{(33)^2}{5} + \frac{(31)^2}{5} \right] - \frac{(110)^2}{15} = 833.2 - 806.67 = 26.53$$

By algebraically transposing the terms in Equation 21.1, the value of SS_{WG} can be computed with Equation 21.4.

$$SS_{WG} = SS_T - SS_{BG} \quad (\text{Equation 21.4})$$

Employing Equation 21.4, the value $SS_{WG} = 22.80$ is computed.

$$SS_{WG} = 49.33 - 26.53 = 22.80$$

Since the value obtained with Equation 21.4 is a function of the values obtained with Equations 21.2 and 21.3, if the computations for either of the latter two equations are incorrect Equation 21.4 will not yield the correct value for SS_{WG} . For this reason, one may prefer to compute the value of SS_{WG} with Equation 21.5.

$$SS_{WG} = \sum_{j=1}^k \left[\Sigma X_j^2 - \frac{(\Sigma X_j)^2}{n_j} \right] \quad (\text{Equation 21.5})$$

The summation sign $\sum_{j=1}^k$ in Equation 21.5 indicates that for each group the value $\Sigma X_j^2 - [(\Sigma X_j)^2/n_j]$ is computed, and the latter values are summed for all k groups. With reference to Example 21.1, Equation 21.5 can be written as follows:

$$SS_{WG} = \left[\Sigma X_1^2 - \frac{(\Sigma X_1)^2}{n_1} \right] + \left[\Sigma X_2^2 - \frac{(\Sigma X_2)^2}{n_2} \right] + \left[\Sigma X_3^2 - \frac{(\Sigma X_3)^2}{n_3} \right]$$

Employing Equation 21.5, the value $SS_{WG} = 22.80$ is computed, which is the same value computed with Equation 21.4.⁷

$$SS_{WG} = \left[426 - \frac{(46)^2}{5} \right] + \left[227 - \frac{(33)^2}{5} \right] + \left[203 - \frac{(31)^2}{5} \right] = 22.80$$

The reader should take note of the fact that the values SS_T , SS_{BG} , and SS_{WG} must always be positive numbers. If a negative value is obtained for any of the aforementioned values, it indicates a computational error has been made.

At this point the values of the **between-groups variance** and the **within-groups variance** can be computed. In the **single-factor between-subjects analysis of variance**, the **between-groups variance** is referred to as the **mean square between-groups**, which is represented by the notation MS_{BG} . MS_{BG} is computed with Equation 21.6.

$$MS_{BG} = \frac{SS_{BG}}{df_{BG}} \quad (\text{Equation 21.6})$$

The **within-groups variance** is referred to as the **mean square within-groups**, which is represented by the notation MS_{WG} . MS_{WG} is computed with Equation 21.7.⁸

$$MS_{WG} = \frac{SS_{WG}}{df_{WG}} \quad (\text{Equation 21.7})$$

Note that a total mean square is not computed.

In order to compute MS_{BG} and MS_{WG} , it is required that the values df_{BG} and df_{WG} (the denominators of Equations 21.6 and 21.7) be computed. df_{BG} , which represents the **between-groups degrees of freedom**, are computed with Equation 21.8.

$$df_{BG} = k - 1 \quad (\text{Equation 21.8})$$

df_{WG} , which represents the **within-groups degrees of freedom**, are computed with Equation 21.9.⁹

$$df_{WG} = N - k \quad (\text{Equation 21.9})$$

Although it is not required in order to determine the F ratio, the **total degrees of freedom** are generally computed, since it can be used to confirm the df values computed with Equations 21.8 and 21.9, as well as the fact that it is employed in the analysis of variance summary table. The total degrees of freedom (represented by the notation df_T), are computed with Equation 21.10.¹⁰

$$df_T = N - 1 \quad (\text{Equation 21.10})$$

The relationship between df_{BG} , df_{WG} , and df_T is described by Equation 21.11.

$$df_T = df_{BG} + df_{WG} \quad (\text{Equation 21.11})$$

Employing Equations 21.8–21.10, the values $df_{BG} = 2$, $df_{WG} = 12$, and $df_T = 14$ are computed. Note that $df_T = df_{BG} + df_{WG} = 2 + 12 = 14$.

$$df_{BG} = 3 - 1 = 2 \quad df_{WG} = 15 - 3 = 12 \quad df_T = 15 - 1 = 14$$

Employing Equations 21.6 and 21.7, the values $MS_{BG} = 13.27$ and $MS_{WG} = 1.9$ are computed.

$$MS_{BG} = \frac{26.53}{2} = 13.27 \quad MS_{WG} = \frac{22.8}{12} = 1.9$$

The F ratio, which is the test statistic for the **single-factor between-subjects analysis of variance**, is computed with Equation 21.12.

$$F = \frac{MS_{BG}}{MS_{WG}} \quad (\text{Equation 21.12})$$

Employing Equation 21.12, the value $F = 6.98$ is computed.

$$F = \frac{13.27}{1.9} = 6.98$$

The reader should take note of the fact that the values MS_{BG} , MS_{WG} , and F must always be positive numbers. If a negative value is obtained for any of the aforementioned values, it indicates a computational error has been made. If $MS_{WG} = 0$, Equation 21.12 will be insoluble. The only time $MS_{WG} = 0$ is when within each group all subjects obtain the same score (i.e., there is no within-groups variability). If all of the groups have the identical mean value, $MS_{BG} = 0$, and if the latter is true, $F = 0$.

V. Interpretation of the Test Results

It is common practice to summarize the results of a **single-factor between-subjects analysis of variance** with the summary table represented by Table 21.2.

Table 21.2 Summary Table of Analysis of Variance for Example 21.1

Source of variation	SS	df	MS	F
Between-groups	26.53	2	13.27	6.98
Within-groups	22.80	12	1.90	
Total	49.33	14		

The obtained value $F = 6.98$ is evaluated with Table A10 (Table of the F Distribution) in the Appendix. In Table A10 critical values are listed in reference to the number of degrees of freedom associated with the numerator and the denominator of the F ratio (i.e., df_{num} and df_{den}).¹¹ In employing the F distribution in reference to Example 21.1, the degrees of freedom for the numerator are $df_{BG} = 2$ and the degrees of freedom for the denominator are $df_{WG} = 12$. In Table A10 the tabled $F_{.95}$ and $F_{.99}$ values are, respectively, employed to evaluate the nondirectional alternative hypothesis H_1 : Not H_0 at the .05 and .01 levels. Throughout the discussion of the analysis of variance the notation $F_{.05}$ is employed to represent the tabled critical F value at the .05 level. The latter value corresponds to the relevant tabled $F_{.95}$ value in Table A10. In the same respect, the notation $F_{.01}$ is employed to represent the tabled critical F value at the .01 level, and corresponds to the relevant tabled $F_{.99}$ value in Table A10.

For $df_{\text{num}} = 2$ and $df_{\text{den}} = 12$, the tabled $F_{.95}$ and $F_{.99}$ values are $F_{.95} = 3.89$ and $F_{.99} = 6.93$. Thus, $F_{.05} = 3.89$ and $F_{.01} = 6.93$. In order to reject the null hypothesis, the obtained F value must be equal to or greater than the tabled critical value at the prespecified level

of significance. Since $F = 6.98$ is greater than $F_{.05} = 3.89$ and $F_{.01} = 6.93$, the alternative hypothesis is supported at both the .05 and .01 levels.

A summary of the analysis of Example 21.1 with the **single-factor between-subjects analysis of variance** follows: It can be concluded that there is a significant difference between at least two of the three groups exposed to different levels of noise. This result can be summarized as follows: $F(2, 12) = 6.98$, $p < .01$.

VI. Additional Analytical Procedures for the Single-Factor Between-Subjects Analysis of Variance and/or Related Tests

1. Comparisons following computation of the omnibus F value for the single-factor between-subjects analysis of variance The F value computed with the analysis of variance is commonly referred to as the **omnibus F value**. The latter term implies that the obtained F value is based on an evaluation of all k group means. Recollect that in order to reject the null hypothesis, it is only required that at least two of the k group means differ significantly from one another. As a result of this, the omnibus F value does not indicate whether just two or, in fact, more than two groups have mean values that differ significantly from one another. In order to answer this question it is necessary to conduct additional tests, which are referred to as **comparisons** (since they involve comparing the means of two or more groups with one another).

Researchers are not in total agreement with respect to the appropriate protocol for conducting comparisons.¹² The basis for the disagreement revolves around the fact that each comparison one conducts increases the likelihood of committing at least one Type I error within a set of comparisons. For this reason, it can be argued that a researcher should employ a lower Type I error rate per comparison to insure that the overall likelihood of committing at least one Type I error in the set of comparisons does not exceed a prespecified alpha value that is reasonably low (e.g., $\alpha = .05$). At this point in the discussion the following two terms are defined: a) The **familywise Type I error rate** (represented by the notation α_{FW}) is the likelihood that there will be at least one Type I error in a **set of c comparisons**;¹³ and b) The **per comparison Type I error rate** (represented by the notation α_{PC}) is the likelihood that any single comparison will result in a Type I error.

Equation 21.13 defines the relationship between the **familywise Type I error rate** and the **per comparison Type I error rate**, where c = the number of comparisons.¹⁴

$$\alpha_{FW} = 1 - (1 - \alpha_{PC})^c \quad \text{(Equation 21.13)}$$

Let us assume that upon computing the value $F = 6.98$ for Example 21.1, the researcher decides to compare each of the three group means with one another — i.e., \bar{X}_1 versus \bar{X}_2 ; \bar{X}_1 versus \bar{X}_3 ; \bar{X}_2 versus \bar{X}_3 . The three aforementioned comparisons can be conceptualized as a **family/set** of comparisons, with $c = 3$. If for each of the comparisons the researcher establishes the value $\alpha_{PC} = .05$, employing Equation 21.13 it can be determined that the **familywise Type I error rate** will equal $\alpha_{FW} = .14$. This result tells the researcher that the likelihood of committing at least one Type I error in the set of three comparisons is .14.

$$\alpha_{FW} = 1 - (1 - .05)^3 = .14$$

Equation 21.14, which is computationally more efficient than Equation 21.13, can be employed to provide an approximation of α_{FW} .¹⁵

$$\alpha_{FW} = (c)(\alpha_{PC}) \quad \text{(Equation 21.14)}$$

Employing Equation 21.14, the value $\alpha_{FW} = .15$ is computed for Example 21.1.

$$\alpha_{FW} = (3)(.05) = .15$$

Note that the **familywise Type I error rate** $\alpha_{FW} = .14$ is almost three times the value of the **per comparison Type I error rate** $\alpha_{PC} = .05$. Of greater importance is the fact that the value $\alpha_{FW} = .14$ is considerably higher than .05, the usual maximum value permitted for a Type I error rate in hypothesis testing. Thus, some researchers would consider the value $\alpha_{FW} = .14$ to be excessive, and if, in fact, a maximum **familywise Type I error rate** of $\alpha_{FW} = .05$ is stipulated by a researcher, it is required that the Type I error rate for each comparison (i.e., α_{PC}) be reduced. Through use of Equation 21.15 or Equation 21.16 (which are, respectively, the algebraic transpositions of Equation 21.13 and Equation 21.14), it can be determined that in order to have $\alpha_{FW} = .05$, the value of α_{PC} must equal .017.¹⁶

$$\alpha_{PC} = 1 - \sqrt[c]{1 - \alpha_{FW}} = 1 - \sqrt[3]{1 - .05} = .017 \quad (\text{Equation 21.15})$$

$$\alpha_{PC} = \frac{\alpha_{FW}}{c} = \frac{.05}{3} = .0167 \quad (\text{Equation 21.16})$$

The reader should take note of the fact that although a reduction in the value of α_{FW} reduces the likelihood of committing a Type I error, it increases the likelihood of committing a Type II error (i.e., not rejecting a false null hypothesis). Thus, as one reduces the value of α_{FW} , the power associated with each of the comparisons that is conducted is reduced. In view of this, it should be apparent that if a researcher elects to adjust the value of α_{FW} , he must consider the impact it will have on the Type I versus Type II error rates for all of the comparisons that are conducted within the set of comparisons.

A number of different strategies have been developed with regard to what a researcher should do about adjusting the **familywise Type I error rate**. These strategies are employed within the framework of the following two types of comparisons that can be conducted following an omnibus F test: **planned comparisons** versus **unplanned comparisons**. The distinction between **planned** and **unplanned comparisons** follows.

Planned comparisons (also known as **a priori comparisons**) **Planned comparisons** are comparisons a researcher plans prior to collecting the data for a study. In a well designed experiment one would expect that a researcher will probably predict differences between specific groups prior to conducting the study. As a result of this, there is general agreement that following the computation of an omnibus F value, a researcher is justified in conducting any comparisons which have been planned beforehand, regardless of whether or not the omnibus F value is significant. Although most sources state that when planned comparisons are conducted it is not necessary to adjust the **familywise Type I error rate**, under certain conditions (such as when there are a large number of planned comparisons) an argument can be made for adjusting the value of α_{FW} .

In actuality, there are two types of planned comparisons that can be conducted, which are referred to as **simple comparisons** versus **complex comparisons**. A **simple comparison** is any comparison in which two groups are compared with one another. For instance: Group 1 versus Group 2 (i.e., \bar{X}_1 versus \bar{X}_2 , which allows one to evaluate the null hypothesis $H_0: \mu_1 = \mu_2$). Simple comparisons are often referred to as **pairwise comparisons**. A **complex comparison** is any comparison in which the combined performance of two or more groups is compared with the performance of one of the other groups or the combined performance of two or more of the other groups. For instance: Group 1 versus the average of Groups 2 and 3 (i.e., \bar{X}_1 versus

$(\bar{X}_2 + \bar{X}_3)/2$, which evaluates the null hypothesis $H_0: \mu_1 = (\mu_2 + \mu_3)/2$. If there are four groups, one can conduct a complex comparison involving the average of Groups 1 and 2 versus the average of Groups 3 and 4 (i.e., $(\bar{X}_1 + \bar{X}_2)/2$ versus $(\bar{X}_3 + \bar{X}_4)/2$, which evaluates the null hypothesis $H_0: (\mu_1 + \mu_2)/2 = (\mu_3 + \mu_4)/2$).

It should be noted that if the omnibus F value is significant, it indicates there is at least one significant difference among all of the possible comparisons that can be conducted. Kirk (1982, 1995) and Maxwell and Delaney (1990), among others, note that in such a situation it is theoretically possible that none of the simple comparisons are significant, and that the one (or perhaps more than one) significant comparison is a complex comparison. It is important to note that regardless of what type of comparisons a researcher conducts, all comparisons should be meaningful within the context of the problem under study, and as, a general rule, comparisons should not be redundant with respect to one another.

Unplanned comparisons (also known as **post hoc**, **multiple**, or a **posteriori** comparisons) An **unplanned comparison** (which can be either a simple or complex comparison) is a comparison a researcher decides to conduct after collecting the data for a study. In conducting **unplanned comparisons**, following the data collection phase of a study a researcher examines the values of the k group means, and at that point decides which groups to compare with one another. Although for many years most researchers argued that unplanned comparisons should not be conducted unless the omnibus F value is significant, more recently many researchers (including this author) have adopted the viewpoint that it is acceptable to conduct unplanned comparisons regardless of whether or not a significant F value is obtained. Although there is general agreement among researchers that the **familywise Type I error rate** should be adjusted when unplanned comparisons are conducted, there is a lack of consensus with regard to the degree of adjustment that is required. This is reflected in the fact that a variety of unplanned comparison procedures have been developed, each of which employs a different method for adjusting the value of α_{FW} . More often than not, when unplanned comparisons are conducted, a researcher will compare each of the k groups with all of the other $(k - 1)$ groups (i.e., all possible comparisons between pairs of groups are made). This “shotgun” approach, which maximizes the number of comparisons conducted, represents the classic situation for which most sources argue it is imperative to control the value of α_{FW} .

The rationale behind the argument that it is more important to adjust the value of α_{FW} in the case of unplanned comparisons as opposed to planned comparisons will be illustrated with a simple example.¹⁷ Let us assume that a set of data is evaluated with an analysis of variance, and a significant omnibus F value is obtained. Let us also assume that within the whole set of data it is possible to conduct 20 comparisons between pairs of means and/or combinations of means. If the truth were known, however, no differences exist between the means of any of the populations being compared. However, in spite of the fact that none of the population means differ, within the set of 20 possible comparisons, one comparison (specifically, the one involving \bar{X}_1 versus \bar{X}_2) results in a significant difference at the .05 level. In this example we will assume that the difference $\bar{X}_1 - \bar{X}_2$ is the largest difference between any pair of means or combination of means in the set of 20 possible comparisons. If, in fact, $\mu_1 = \mu_2$, a significant result obtained for the comparison \bar{X}_1 versus \bar{X}_2 will represent a Type I error.

Let us assume that the comparison \bar{X}_1 versus \bar{X}_2 is planned beforehand, and it is the only comparison the researcher intends to make. Since there are 20 possible comparisons, the researcher has only a 1 in 20 chance (i.e., .05) of conducting the comparison Group 1 versus Group 2, and in the process commits a Type I error. If, on the other hand, the researcher does not plan any comparisons beforehand, but after computing the omnibus F value decides to make all 20 possible comparisons, he has a 100% chance of making a Type I error, since it is certain he will compare Groups 1 and 2. Even if the researcher decides to make only one unplanned

comparison — specifically, the one involving the largest difference between any pair of means or combination of means — he will also have a 100% chance of committing a Type I error, since the comparison he will make will be \bar{X}_1 versus \bar{X}_2 . This example illustrates that from a probabilistic viewpoint, the **familywise Type I error rate** associated with a set of unplanned comparisons will be higher than the rate for a set of planned comparisons.

The remainder of this section will describe the most commonly recommended comparison procedures. Specifically, the following procedures will be described: a) **Linear contrasts**; b) **Multiple t tests/Fisher's LSD test**; c) **The Bonferroni–Dunn test**; d) **Tukey's HSD test**; e) **The Newman–Keuls test**; f) **The Scheffé test**; and g) **The Dunnett test**. Although any of the aforementioned comparison procedures can be used for both planned and unplanned comparisons, **linear contrasts** and **multiple t tests/Fisher's LSD test** (which do not control the value of α_{FW}) are generally described within the context of planned comparisons. Some sources, however, do employ the latter procedures for unplanned comparisons. The **Bonferroni–Dunn test**, **Tukey's HSD test**, the **Newman–Keuls test**, the **Scheffé test**, and the **Dunnett test** are generally described as unplanned comparison procedures that are employed when a researcher wants to control the value of α_{FW} . The point that will be emphasized throughout the discussion to follow is that the overriding issue in selecting a comparison procedure is whether or not the researcher wants to control the value of α_{FW} , and if so, to what degree. This latter issue is essentially what determines the difference between the various comparison procedures to be described in this section.

Linear contrasts **Linear contrasts** (which are almost always described within the framework of planned comparisons) are comparisons that involve a linear combination of population means. In the case of a simple comparison, a **linear contrast** consists of comparing two of the group means with one another (e.g., \bar{X}_1 versus \bar{X}_2). In the case of a complex comparison, the combined performance of two or more groups is compared with the performance of one of the other groups or the combined performance of two or more of the other groups (e.g., \bar{X}_1 versus $(\bar{X}_2 + \bar{X}_3)/2$). In conducting both simple and complex comparisons, the researcher must assign weights, which are referred to as **coefficients**, to all of the group means. These coefficients reflect the relative contribution of each of the group means to the two mean values that are being contrasted with one another in the comparison. In the case of a complex comparison, at least one of the two mean values that are contrasted in the comparison will be based on a weighted combination of the means of two or more of the groups.

The use of **linear contrasts** will be described for both simple and complex comparisons. In the examples that will be employed to illustrate **linear contrasts**, it will be assumed that all comparisons are planned beforehand, and that the researcher is making no attempt to control the value of α_{FW} . Thus, for each comparison to be conducted it will be assumed that $\alpha_{PC} = .05$. All of the comparisons (both simple and complex) to be described in this section are referred to as **single degree of freedom (df) comparisons**. This is the case, since one degree of freedom is always employed in the numerator of the F ratio (which represents the test statistic for a comparison).¹⁸

Linear contrast of a planned simple comparison Let us assume that prior to obtaining the data for Example 21.1, the experimenter hypothesizes there will be a significant difference between Group 1 (**no noise**) and Group 2 (**moderate noise**). After conducting the omnibus F test, the simple planned comparison \bar{X}_1 versus \bar{X}_2 is conducted to compare the performance of the two groups. The null and alternative hypotheses for the comparison follow: $H_0: \mu_1 = \mu_2$ versus $H_1: \mu_1 \neq \mu_2$.¹⁹ Table 21.3 summarizes the information required to conduct the planned comparison \bar{X}_1 versus \bar{X}_2 .

Table 21.3 Planned Simple Comparison: Group 1 Versus Group 2

Group	\bar{X}_j	Coefficient (c_j)	Product ($c_j(\bar{X}_j)$)	Squared Coefficient (c_j^2)
1	9.2	+1	(+1)(9.2) = +9.2	1
2	6.6	-1	(-1)(6.6) = -6.6	1
3	6.2	0	(0)(6.2) = 0	0
		$\Sigma c_j = 0$	$\Sigma(c_j)(\bar{X}_j) = 2.6$	$\Sigma c_j^2 = 2$

The following should be noted with respect to Table 21.3: a) The rows of Table 21.3 represent data for each of the three groups employed in the experiment. Even though the comparison involves two of the three groups, the data for all three groups are included to illustrate how the group which is not involved in the comparison is eliminated from the calculations; b) Column 2 contains the mean score of each of the groups; c) In Column 3 each of the groups is assigned a **coefficient**, represented by the notation c_j . The value of c_j assigned to each group is a weight that reflects the proportional contribution of the group to the comparison. Any group not involved in the comparison (in this instance Group 3) is assigned a coefficient of zero. Thus, $c_3 = 0$. When only two groups are involved in a comparison, one of the groups (it does not matter which one) is assigned a coefficient of +1 (in this instance Group 1 is assigned the coefficient $c_1 = +1$) and the other group a coefficient of -1 (i.e., $c_2 = -1$). Note that Σc_j , the sum of the coefficients (which is the sum of Column 3), must always equal zero (i.e., $c_1 + c_2 + c_3 = (+1) + (-1) + 0 = 0$); d) In Column 4 a product is obtained for each group. The product for a group is obtained by multiplying the mean of the group (\bar{X}_j) by the coefficient that has been assigned to that group (c_j). Although it may not be immediately apparent from looking at the table, the sum of Column 4, $\Sigma(c_j)(\bar{X}_j)$, is, in fact, the difference between the two means being compared (i.e., $\Sigma(c_j)(\bar{X}_j)$ is equal to $\bar{X}_1 - \bar{X}_2 = 9.2 - 6.6 = 2.6$);²⁰ and e) Σc_j^2 , the sum of Column 5, is the sum of the squared coefficients.

The test statistic for the comparison is an F ratio, represented by the notation F_{comp} . In order to compute the value F_{comp} , a **sum of squares** (SS_{comp}), a **degrees of freedom value** (df_{comp}), and a **mean square** (MS_{comp}) for the comparison must be computed. The **comparison sum of squares** (SS_{comp}) is computed with Equation 21.17. Note that Equation 21.17 assumes there are an equal number of subjects (n) in each group.²¹

$$SS_{\text{comp}} = \frac{n[\Sigma(c_j)(\bar{X}_j)]^2}{\Sigma c_j^2} \quad (\text{Equation 21.17})$$

Substituting the appropriate values from Example 21.1 in Equation 21.17, the value $SS_{\text{comp}} = 16.9$ is computed.

$$SS_{\text{comp}} = \frac{5(2.6)^2}{2} = 16.9$$

The **comparison mean square** (MS_{comp}) is computed with Equation 21.18. MS_{comp} represents a measure of between-groups variability which takes into account just the two group means involved in the comparison.

$$MS_{\text{comp}} = \frac{SS_{\text{comp}}}{df_{\text{comp}}} \quad (\text{Equation 21.18})$$

In a **single degree of freedom comparison**, df_{comp} will always equal 1 since the number of mean values being compared in such a comparison will always be $k_{\text{comp}} = 2$, and $df_{\text{comp}} = k_{\text{comp}} - 1 = 2 - 1 = 1$. Substituting the values $SS_{\text{comp}} = 16.9$ and $df_{\text{comp}} = 1$ in Equation 21.18, the value $MS_{\text{comp}} = 16.9$ is computed. Note that since in a **single degree of freedom comparison** the value of df_{comp} will always equal 1, the values SS_{comp} and MS_{comp} will always be equivalent.

$$MS_{\text{comp}} = \frac{16.9}{1} = 16.9$$

The test statistic F_{comp} is computed with Equation 21.19. F_{comp} is a ratio that is comprised of the variability of the two means involved in the comparison divided by the within-groups variability employed for the omnibus F test.²²

$$F_{\text{comp}} = \frac{MS_{\text{comp}}}{MS_{\text{WG}}} \quad (\text{Equation 21.19})$$

Substituting the values $MS_{\text{comp}} = 16.9$ and $MS_{\text{WG}} = 1.9$ in Equation 21.19, the value $F_{\text{comp}} = 8.89$ is computed.

$$F_{\text{comp}} = \frac{16.9}{1.9} = 8.89$$

The value $F_{\text{comp}} = 8.89$ is evaluated with **Table A10**. Employing **Table A10**, the appropriate degrees of freedom value for the numerator is $df_{\text{num}} = 1$. This is the case, since the numerator of the F_{comp} ratio is MS_{comp} , and the degrees of freedom associated with the latter value is $df_{\text{comp}} = 1$. The denominator degrees of freedom will be the value of df_{WG} employed for the omnibus F test, which for Example 21.1 is $df_{\text{WG}} = 12$.

For $df_{\text{num}} = 1$ and $df_{\text{den}} = 12$, the tabled critical .05 and .01 F values are $F_{.05} = 4.75$ and $F_{.01} = 9.33$. Since the obtained value $F_{\text{comp}} = 8.89$ is greater than $F_{.05} = 4.75$, the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is supported at the .05 level. Since $F_{\text{comp}} = 8.89$ is less than $F_{.01} = 9.33$, the latter alternative hypothesis is not supported at the .01 level. Thus, if the value $\alpha = .05$ is employed, the researcher can conclude that Group 1 recalled a significantly greater number of nonsense syllables than Group 2.

With respect to Example 21.1, it is possible to conduct the following additional simple comparisons: \bar{X}_1 versus \bar{X}_3 ; \bar{X}_2 versus \bar{X}_3 . The latter two simple comparisons will be conducted later employing **multiple t tests/Fisher's LSD test** (which, as will be noted, are computationally equivalent to the **linear contrast** procedure described in this section).

Linear contrast of a planned complex comparison Let us assume that prior to obtaining the data for Example 21.1, the experimenter hypothesizes there will be a significant difference between the performance of Group 3 (**extreme noise**) and the combined performance of Group 1 (**no noise**) and Group 2 (**moderate noise**). Such a comparison is a complex comparison, since it involves a single group being contrasted with two other groups. As is the case with the simple comparison \bar{X}_1 versus \bar{X}_2 , two means are also contrasted within the framework of the complex comparison. However, one of the two means is a composite mean that is based upon the combined performance of two groups. The complex comparison represents a single degree of freedom comparison. This is the case, since two means are being contrasted with one another — specifically, the mean of Group 3 with the composite mean of Groups 1 and 2. The fact

that it is a single degree of freedom comparison is also reflected in the fact that there is one equals sign (=) in both the null and alternative hypotheses for the comparison. The null and alternative hypotheses for the complex comparison are $H_0: \mu_3 = (\mu_1 + \mu_2)/2$ versus $H_1: \mu_3 \neq (\mu_1 + \mu_2)/2$.²³ Table 21.4 summarizes the information required to conduct the planned complex comparison \bar{X}_3 versus $(\bar{X}_1 + \bar{X}_2)/2$.

Table 21.4 Planned Complex Comparison: Group 3 Versus Groups 1 and 2

Group	(\bar{X}_j)	Coefficient (c_j)	Product ($c_j)(\bar{X}_j)$	Squared Coefficient (c_j^2)
1	9.2	$-\frac{1}{2}$	$\left(-\frac{1}{2}\right)(9.2) = -4.6$	$\frac{1}{4}$
2	6.6	$-\frac{1}{2}$	$\left(-\frac{1}{2}\right)(6.6) = -3.3$	$\frac{1}{4}$
3	6.2	+1	$(+1)(6.2) = +6.2$	1
		$\Sigma c_j = 0$	$\Sigma(c_j)(\bar{X}_j) = -1.7$	$\Sigma c_j^2 = 1.5$

Note that the first two columns of Table 21.4 are identical to the first two columns of Table 21.3. The different values in the remaining columns of Table 21.4 result from the fact that different coefficients are employed for the complex comparison. The absolute value of $\Sigma(c_j)(\bar{X}_j) = -1.7$ represents the difference between the two sets of means contrasted in the null hypothesis — specifically, the difference between $\bar{X}_3 = 6.2$ and the composite mean of Group 1 ($\bar{X}_1 = 9.2$) and Group 2 ($\bar{X}_2 = 6.6$). The latter composite mean will be represented with the notation $\bar{X}_{1/2}$. Since $\bar{X}_{1/2} = (9.2 + 6.6)/2 = 7.9$, the difference between the two means evaluated with the comparison is $6.2 - 7.9 = -1.7$ (which is the same as the value $\Sigma(c_j)(\bar{X}_j) = -1.7$, which is the sum of Column 4 in Table 21.4).

Before conducting the computations for the complex comparison, a general protocol will be described for assigning coefficients to the groups involved in either a simple or complex comparison. Within the framework of describing the protocol, it will be employed to determine the coefficients for the complex comparison under discussion.

1) Write out the null hypothesis (i.e., $H_0: \mu_3 = (\mu_1 + \mu_2)/2$). Any group not involved in the comparison (i.e., not noted in the null hypothesis) is assigned a coefficient of zero. Since all three groups are included in the present comparison, none of the groups receives a coefficient of zero.

2) On each side of the equals sign of the null hypothesis write the number of group means designated in the null hypothesis. Thus:

$$H_0: \mu_3 = \frac{\mu_1 + \mu_2}{2}$$

1 mean 2 means

3) To obtain the coefficient for each of the groups included in the null hypothesis, employ Equation 21.20. The latter equation, which is applied to each side of the null hypothesis, represents the reciprocal of the number of means on a specified side of the null hypothesis.²⁴

$$\text{Coefficient} = \frac{1}{\text{Number of group means}} \quad (\text{Equation 21.20})$$

Since there is only one mean to the left of the equals sign (μ_3), employing Equation 21.20 we determine that the coefficient for that group (Group 3) equals $\frac{1}{1} = 1$. Since there are two means to the right of the equals sign (μ_1 and μ_2), using Equation 21.20 we determine the coefficient for both of the groups to the right of the equals sign (Groups 1 and 2) equals $\frac{1}{2}$. Notice that all groups on the same side of the equals sign receive the same coefficient.²⁵

4) The coefficient(s) on one side of the equals sign are assigned a positive sign, and the coefficient(s) on the other side of the equals sign are assigned a negative sign. Equivalent results will be obtained irrespective of which side of the equals sign is assigned positive versus negative coefficients. In the complex comparison under discussion, a positive sign is assigned to the coefficient to the left of the equals sign, and negative signs are assigned to coefficients to the right of the equals sign. Thus, the values of the coefficients are: $c_1 = -1/2$; $c_2 = -1/2$; $c_3 = +1$. Note that the sum of the coefficients must always equal zero (i.e., $c_1 + c_2 + c_3 = (-1/2) + (-1/2) + (+1)$).²⁶

Equations 21.17–21.19, which are employed for the simple comparison, are also used to evaluate a complex comparison. Substituting the appropriate information from Table 21.4 in Equation 21.17, the value $SS_{\text{comp}} = 9.63$ is computed.

$$SS_{\text{comp}} = \frac{5(-1.7)^2}{1.5} = 9.63$$

Employing Equation 21.18, the value $MS_{\text{comp}} = 9.63$ is computed. Note that since the complex comparison is a single degree of freedom comparison, $df_{\text{comp}} = 1$.

$$MS_{\text{comp}} = \frac{9.63}{1} = 9.63$$

Employing Equation 21.19, the value $F_{\text{comp}} = 5.07$ is computed.

$$F_{\text{comp}} = \frac{9.63}{1.9} = 5.07$$

The protocol for evaluating the value $F_{\text{comp}} = 5.07$ computed for the complex comparison is identical to that employed for the simple comparison. In determining the tabled critical F value in Table A10, the same degrees of freedom values are employed. This is the case since the numerator degrees of freedom for any single degree of freedom comparison is $df_{\text{comp}} = 1$. The denominator degrees of freedom is df_{WG} , which, as in the case of the simple comparison, is the value of df_{WG} employed for the omnibus F test. Thus, the appropriate degrees of freedom for the complex comparison are $df_{\text{num}} = 1$ and $df_{\text{den}} = 12$. The tabled critical .05 and .01 F values in Table A10 for the latter degrees of freedom are $F_{.05} = 4.75$ and $F_{.01} = 9.33$. Since the obtained value $F = 5.07$ is greater than $F_{.05} = 4.75$, the nondirectional alternative hypothesis $H_1: \mu_3 \neq (\mu_1 + \mu_2)/2$ is supported at the .05 level. Since $F = 5.07$ is less than $F_{.01} = 9.33$, the latter alternative hypothesis is not supported at the .01 level. Thus, if the value $\alpha = .05$ is employed, the researcher can conclude that Group 3 recalled a significantly fewer number of nonsense syllables than the average number recalled when the performance of Groups 1 and 2 are combined.

Orthogonal comparisons Most sources agree that intelligently planned studies involve a limited number of meaningful comparisons which the researcher plans prior to collecting the data. As a general rule, any comparisons that are conducted should address critical questions underlying

the general hypothesis under study. Some researchers believe that it is not even necessary to obtain an omnibus F value if, in fact, the critical information one is concerned with is contained within the framework of the planned comparisons. It is generally recommended that the maximum number of planned comparisons one conducts should not exceed the value of df_{BG} employed for the omnibus F test. If the number of planned comparisons is equal to or less than df_{BG} , sources generally agree that a researcher is not obliged to adjust the value of α_{FW} . When, however, the number of planned comparisons exceeds df_{BG} , many sources recommend that the value of α_{FW} be adjusted. Applying this protocol to Example 21.1, since $df_{BG} = 2$, one can conduct two planned comparisons without being obliged to adjust the value of α_{FW} .

The subject of **orthogonal comparisons** is relevant to the general question of how many (and specifically which) comparisons a researcher should conduct. Orthogonal comparisons are defined as comparisons that are independent of one another. In other words, such comparisons are not redundant, in that they do not overlap with respect to the information they provide. In point of fact, the two comparisons that have been conducted (i.e., the simple comparison of Group 1 versus Group 2, and the complex comparison of Group 3 versus the combined performance of Groups 1 and 2) are orthogonal comparisons. This can be demonstrated by employing Equation 21.21, which defines the relationship that will exist between two comparisons if they are orthogonal to one another. In Equation 21.21, c_{j1} is the coefficient assigned to Group j in Comparison 1 and c_{j2} is the coefficient assigned to Group j in Comparison 2. If, in fact, two comparisons are orthogonal, the sum of the products of the coefficients of all of k groups will equal zero.

$$\sum_{j=1}^k (c_{j1})(c_{j2}) = 0 \quad \text{(Equation 21.21)}$$

Equation 21.21 is employed below with the two comparisons that have been conducted in this section. Notice that for each group, the first value in the parentheses is the coefficient for that group for the simple comparison (Group 1 versus Group 2), while the second value in parentheses is the coefficient for that group for the complex comparison (Group 3 versus Groups 1 and 2).

$$\begin{array}{ccc} \text{Group 1} & \text{Group 2} & \text{Group 3} \\ (+1)\left(-\frac{1}{2}\right) + (-1)\left(-\frac{1}{2}\right) + (0)(+1) & = & \left(-\frac{1}{2}\right) + \left(+\frac{1}{2}\right) + 0 = 0 \end{array}$$

If there are k treatments, there will be $(k - 1)$ (which corresponds to df_{BG} employed for the omnibus F test) orthogonal comparisons (also known as **orthogonal contrasts**) within each complete orthogonal set. This is illustrated by the fact that two comparisons comprise the orthogonal set demonstrated above — specifically, Group 1 versus Group 2, and Group 3 versus Groups 1 and 2. Actually, when (as is the case in Example 21.1) there are $k = 3$ treatments, there are three possible sets of orthogonal comparisons — each set being comprised of one simple comparison and one complex comparison. In addition to the set noted above, the following two additional orthogonal sets can be formed: a) Group 1 versus Group 3; Group 2 versus Groups 1 and 3; b) Group 2 versus Group 3; Group 1 versus Groups 2 and 3.

When $k > 3$ there will be more than 2 contrasts in a set of orthogonal contrasts. Within that full set of orthogonal contrasts, if the coefficients from any two of the contrasts are substituted in Equation 21.21, they will yield a value of zero. It should also be noted that the number of possible sets of contrasts will increase as the value of k increases. It is important to note, however, that when all possible sets of contrasts are considered, most of them will not be orthogonal. With respect to determining those contrasts that are orthogonal, Howell (1992, 1997)

describes a simple protocol that can be employed to derive most (although not all) orthogonal contrasts in a body of data. The procedure described by Howell (1992, 1997) is summarized in Figure 21.1.

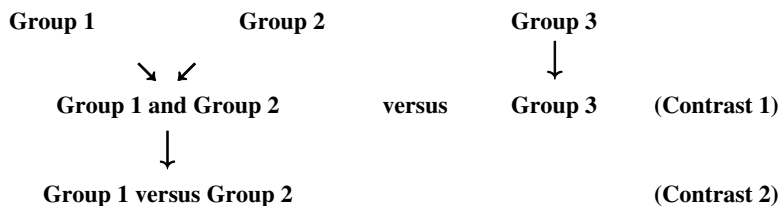


Figure 21.1 Tree Diagram for Determining Orthogonal Contrasts

In employing Figure 21.1, initially two blocks of groups are formed employing all k groups. A block can be comprised of one or more of the groups. In Figure 21.1, the first block is comprised of Groups 1 and 2, and the second block of Group 3. This will represent the first contrast, which corresponds to the complex comparison that is described in this section. Any blocks that remain which are comprised of two or more groups are broken down into smaller blocks. Thus, the block comprised of the Group 1 and Group 2 is broken down into two blocks, each consisting of one group. The contrast of these two groups (Group 1 versus Group 2) represents the second contrast in the orthogonal set.

Figure 21.1 can also be employed to derive the other two possible orthogonal sets for Example 21.1. To illustrate, the initial two blocks derived can be a block consisting of Groups 1 and 3 and a second block consisting of Group 2. This represents the complex comparison of Group 2 versus Groups 1 and 3. The remaining block consisting of Groups 1 and 3 can be broken down into two blocks consisting of Group 1 and Group 3. The comparison of these two groups, which represents a simple comparison, constitutes the second comparison in that orthogonal set.

Note that once a group has been assigned to a block, and that block is compared to an adjacent block, from that point on any other comparisons involving that group will be with other groups that fall within its own block. Thus, in our example, if the first comparison is Groups 1 and 2 versus Group 3, the researcher cannot use the comparison Group 1 versus Group 3 as the second comparison for that set, since the two groups are in different blocks. If the latter comparison is conducted, the sum of the products of the coefficients of all k groups for the two comparisons will not equal zero, and thus not constitute an orthogonal set. To illustrate this latter fact, the coefficients of the three groups for the simple comparison depicted in Table 21.3 are rearranged as follows: $c_1 = +1$, $c_2 = 0$, and $c_3 = -1$. The latter coefficients are employed if the simple comparison Group 1 versus Group 3 is conducted. Equation 21.21 is now employed to demonstrate that the Group 1 versus Group 3 comparison is not orthogonal to the complex comparison Group 3 versus Groups 1 and 2 summarized in Table 21.4.

$$\begin{array}{ccc} \text{Group 1} & \text{Group 2} & \text{Group 3} \\ (+1)\left(-\frac{1}{2}\right) & + \quad (0)\left(-\frac{1}{2}\right) & + \quad (-1)(+1) = \left(-\frac{1}{2}\right) + 0 + (-1) = -1\frac{1}{2} \end{array}$$

It should be pointed out that when more than one set of orthogonal comparisons are conducted, since the different sets are not orthogonal to one another, many of the comparisons one conducts will not be independent of one another. For this reason, a researcher who does not want to conduct any nonindependent comparisons should only conduct those comparisons involving the orthogonal set which provide the most meaningful information with regard to the hypothesis

under study. It should be noted, however, that there is no immutable rule that states that a researcher can only conduct orthogonal comparisons. Many sources point out there are times when the questions addressed by nonorthogonal comparisons can often contribute to a researcher's understanding of the general hypothesis under study.

Another characteristic of orthogonal comparisons is that the sum of squares for all comparisons that comprise a set of orthogonal comparisons equals the value of SS_{BG} for the omnibus F test. This reflects the fact that the variability in a set of orthogonal contrasts will account for all the between-groups variability in the full set of data. Employing the data for the simple comparison summarized in Table 21.3 and the complex comparison summarized in Table 21.4, it is confirmed below that the sum of squares for the latter two comparisons (which comprise an orthogonal set) equals the value $SS_{BG} = 26.53$ obtained with Equation 21.3.

$$SS_{BG} = 26.53 = SS_{\text{simple comparison}} + SS_{\text{complex comparison}} = 16.9 + 9.63 = 26.53$$

Test 21a: Multiple t tests/Fisher's LSD test One option a researcher has available after computing an omnibus F value is to run **multiple t tests** (specifically, the **t test for two independent samples**), in order to determine whether there is a significant difference between any of the pairs of means that can be contrasted within the framework of either simple or complex comparisons. In point of fact, it can be algebraically demonstrated that in the case of both simple and complex comparisons, the use of **multiple t tests** will yield a result that is equivalent to that obtained with the protocol described for conducting **linear contrasts**. When **multiple t tests** are discussed as a procedure for conducting comparisons, most sources state that: a) **Multiple t tests** should only be employed for planned comparisons; b) Since **multiple t tests** are only employed for planned comparisons, they can be conducted regardless of whether or not the omnibus F value is significant; and c) In conducting **multiple t tests** for planned comparisons, the researcher is not required to adjust the value of α_{FW} , as long as a limited number of comparisons are conducted (as noted earlier, most sources state the number of planned comparisons should not exceed df_{BG}). All of the aforementioned stipulations noted for **multiple t tests** also apply to **linear contrasts** (since as noted above, **multiple t tests** and **linear contrasts** are computationally equivalent).

When, on the other hand, comparisons are unplanned and **multiple t tests** are employed to compare pairs of means, the use of **multiple t tests** within the latter context is referred to as **Fisher's LSD test** (the term **LSD** is an abbreviation for **least significant difference**). When **Fisher's LSD test** is compared with other unplanned comparison procedures, it provides the most powerful test with respect to identifying differences between pairs of means, since it does not adjust the value of α_{FW} . Of all the unplanned comparison procedures, **Fisher's LSD test** requires the smallest difference between two means in order to conclude that a difference is significant. However, since **Fisher's LSD test** does not reduce the value of α_{FW} , it has the highest likelihood of committing one or more Type I errors in a set/family of comparisons. In the discussion to follow, since **multiple t tests** and **Fisher's LSD method** are computationally equivalent (as well as equivalent to **linear contrasts**), the term **multiple t tests/Fisher's LSD test** will refer to a computational procedure which can be employed for both planned and unplanned comparisons that does not adjust the value of α_{FW} .

Equation 21.22 can be employed to compute the test statistic (which employs the t distribution) for **multiple t tests/Fisher's LSD test**. Whereas Equation 21.22 can only be employed for simple comparisons, Equation 21.23 is a generic equation that can be employed for both simple and complex comparisons. It will be assumed that the null and alternative hypotheses for any comparisons being conducted are as follows: $H_0: \mu_a = \mu_b$ versus $H_1: \mu_a \neq \mu_b$.

$$t = \frac{\bar{X}_a - \bar{X}_b}{\sqrt{\frac{2MS_{WG}}{n}}} \quad (\text{Equation 21.22})$$

Where: \bar{X}_a and \bar{X}_b represent the two means contrasted in the comparison

$$t = \frac{\bar{X}_a - \bar{X}_b}{\sqrt{\frac{(\sum c_j^2)(MS_{WG})}{n}}} \quad (\text{Equation 21.23})$$

In the case of a **simple comparison**, the value $\sum c_j^2$ in Equation 21.23 will always equal 2, thus resulting in Equation 21.22.²⁷

The degrees of freedom employed in evaluating the t value computed with Equations 21.22 and 21.23 is the value of df_{WG} computed for the omnibus F test. Thus, in the case of Example 21.1, the value $df_{WG} = 12$ is employed. Note that in Equations 21.22/21.23, the value MS_{WG} computed for the omnibus F test is employed in computing the **standard error of the difference** in the denominator of the t test equation, as opposed to the value $\sqrt{(\bar{s}_a^2/n_a) + (\bar{s}_b^2/n_b)}$, which is employed in Equation 11.1 (the equation for the **t test for two independent samples** when $n_a = n_b$). This is the case, since MS_{WG} is a pooled estimate of the population variance based on the full data set (i.e., the k groups for which the omnibus F value is computed).²⁸

Equation 21.22 is employed below to conduct the simple comparison of Group 1 versus Group 2.

$$t = \frac{9.2 - 6.6}{\sqrt{\frac{(2)(1.9)}{5}}} = 2.99$$

The obtained value $t = 2.99$ is evaluated with **Table A2 (Table of Student's t Distribution)** in the **Appendix**. For $df = 12$, the tabled critical two-tailed .05 and .01 values are $t_{.05} = 2.18$ and $t_{.01} = 3.06$. Since $t = 2.99$ is greater than $t_{.05} = 2.18$, the nondirectional alternative hypothesis $H_1: \mu_a \neq \mu_b$ is supported at the .05 level. Since $t = 2.99$ is less than $t_{.01} = 3.06$, the latter alternative hypothesis is not supported at the .01 level. Thus, if $\alpha = .05$, the researcher can conclude that Group 1 recalled a significantly greater number of nonsense syllables than Group 2. This result is consistent with that obtained in the previous section using the protocol for **linear contrasts**.

Equation 21.24 employs **multiple t tests/Fisher's LSD test** to compute the minimum required difference in order for two means to differ significantly from one another at a pre-specified level of significance. The latter value is represented by the notation CD_{LSD} , with CD being the abbreviation for **critical difference**. Whereas Equation 21.24 only applies to simple comparisons, Equation 21.25 is a generic equation that can be employed for both simple and complex comparisons.²⁹

$$CD_{LSD} = \sqrt{F_{(1, WG)}} \sqrt{\frac{2MS_{WG}}{n}} \quad (\text{Equation 21.24})$$

$$CD_{LSD} = \sqrt{F_{(1, WG)}} \sqrt{\frac{(\sum c_j^2)(MS_{WG})}{n}} \quad (\text{Equation 21.25})$$

Where: $F_{(1, WG)}$ is the tabled critical F value for $df_{\text{num}} = 1$ and $df_{\text{den}} = df_{WG}$ at the prespecified level of significance³⁰

Employing the appropriate values from Example 21.1 in Equation 21.24, the value $CD_{LSD} = 1.90$ is computed.³¹

$$CD_{LSD} = \sqrt{4.75} \sqrt{\frac{(2)(1.9)}{5}} = 1.90$$

Thus, in order to differ significantly at the .05 level, the means of any two groups must differ from one another by at least 1.90 units. Employing [Table 21.5](#), which summarizes the differences between pairs of means involving all three experimental groups, it can be seen that the following simple comparisons are significant at the .05 level if **multiple t tests/Fisher's LSD test** are employed: $\bar{X}_1 - \bar{X}_2 = 2.6$; $\bar{X}_1 - \bar{X}_3 = 3$. The difference $\bar{X}_2 - \bar{X}_3 = .4$ is not significant, since it is less than $CD_{LSD} = 1.90$.

Within the framework of the discussion to follow, it will be demonstrated that the CD value computed with **multiple t tests/Fisher's LSD test** is the smallest CD value that can be computed with any of the comparison methods that can be employed for the analysis of variance.

Table 21.5 Differences Between Pairs of Means in Example 21.1

$\bar{X}_1 - \bar{X}_2 = 9.2 - 6.6 = 2.6$
$\bar{X}_1 - \bar{X}_3 = 9.2 - 6.2 = 3.0$
$\bar{X}_2 - \bar{X}_3 = 6.6 - 6.2 = 0.4$

Multiple t tests/Fisher's LSD test will now be demonstrated for a complex comparison. Equations 21.23 and 21.25 are employed to evaluate the complex comparison involving the mean of Group 3 versus the composite mean of Groups 1 and 2. Employing Equation 21.23, the absolute value $t = 2.25$ is computed.³² The value $CD_{LSD} = 1.65$ is computed with Equation 21.25. Note that in computing the values of t and CD_{LSD} , the value $\sum c_j^2 = 1.5$ is employed in Equations 21.23 and 21.25, as opposed to $\sum c_j^2 = 2$, which is employed in Equations 21.22 and 21.24. This latter fact accounts for why the value $CD_{LSD} = 1.65$ computed for the complex comparison is smaller than the value $CD_{LSD} = 1.90$ computed for the simple comparison.

$$t = \frac{6.2 - 7.9}{\sqrt{\frac{(1.5)(1.9)}{5}}} = -2.25$$

$$CD_{LSD} = \sqrt{4.75} \sqrt{\frac{(1.5)(1.9)}{5}} = 1.65$$

Since the obtained absolute value $t = 2.25$ is greater than $t_{.05} = 2.18$ (which is the tabled critical two-tailed .05 t value for $df_{WG} = 12$), the nondirectional alternative hypothesis

$H_1: \mu_3 \neq (\mu_1 + \mu_2)/2$ is supported at the .05 level. Since $t = 2.25$ is less than the tabled critical two-tailed value $t_{.01} = 3.06$, the latter alternative hypothesis is not supported at the .01 level. Thus, if $\alpha = .05$, the researcher can conclude that Group 3 recalled a significantly fewer number of nonsense syllables than the average number recalled when the performances of Groups 1 and 2 are combined. This result is consistent with that obtained in the previous section using the protocol for **linear contrasts**.

The fact that the obtained absolute value of the difference $|\bar{X}_3 - \bar{X}_{1/2}| = |6.2 - 7.9| = 1.7$ is larger than the computed value $CD_{LSD} = 1.65$, is consistent with the fact that the difference for the **complex comparison** is significant at the .05 level. The computed value $CD_{LSD} = 1.65$ indicates that for any complex comparison involving the set of coefficients employed in Table 21.4, the minimum required difference in order for the two mean values stipulated in the null hypothesis to differ significantly from one another at the .05 level is $CD_{LSD} = 1.65$.

Test 21b: The Bonferroni–Dunn test First formally described by Dunn (1961), the **Bonferroni–Dunn test** is based on the **Bonferroni inequality**, which states that the probability of the occurrence of a set of events can never be greater than the sum of the individual probabilities for each event. Although the **Bonferroni–Dunn test** is identified in most sources as a planned comparison procedure, it can also be employed for unplanned comparisons. In actuality, the **Bonferroni–Dunn test** is computationally identical to **multiple t tests/Fisher’s LSD test/linear contrasts**, except for the fact that the equation for the test statistic employs an adjustment in order to reduce the value of α_{FW} . By virtue of reducing α_{FW} , the power of the **Bonferroni–Dunn test** will always be less than the power associated with **multiple t tests/Fisher’s LSD test/linear contrasts** (since the latter procedure does not adjust the value of α_{FW}). As a general rule, whenever the **Bonferroni–Dunn test** is employed to conduct all possible pairwise comparisons in a set of data, it provides the least powerful test of an alternative hypothesis of all the available comparison procedures.

The **Bonferroni–Dunn test** requires a researcher to initially stipulate the highest **familywise Type I error rate** he is willing to tolerate. For purposes of illustration, let us assume that in conducting comparisons in reference to Example 21.1 the researcher does not want the value of α_{FW} to exceed .05 (i.e., he does not want more than a 5% chance of committing at least one Type I error in a set of comparisons). Let us also assume he either plans beforehand or decides after computing the omnibus F value, that he will compare each of the group means with one another. This will result in the following three simple comparisons: Group 1 versus Group 2; Group 1 versus Group 3; Group 2 versus Group 3. To insure that the **familywise Type I error rate** does not exceed .05, $\alpha_{FW} = .05$ is divided by $c = 3$, which represents the number of comparisons that comprise the set. The resulting value $\alpha_{PC} = \alpha_{FW}/c = .05/3 = .0167$ represents for each of the comparisons that are conducted, the likelihood of committing a Type I error. Thus, even if a Type I error is made for all three of the comparisons, the overall **familywise Type I error rate** will not exceed .05 (since $(3)(.0167) = .05$).

In the case of a simple comparison, Equation 21.26 is employed to compute $CD_{B/D}$, which will represent the **Bonferroni–Dunn test** statistic. $CD_{B/D}$ is the minimum required difference in order for two means to differ significantly from one another, if the familywise Type I error rate is set at a prespecified level.³³

$$CD_{B/D} = t_{B/D} \sqrt{\frac{2MS_{WG}}{n}} \quad \text{(Equation 21.26)}$$

The value $t_{B/D}$ in Equation 21.26 represents the tabled critical t value at the level of significance that corresponds to the value of α_{PC} (which in this case equals $t_{.0167}$) for df_{WG} (which

for Example 21.1 is $df_{WG} = 12$). The value of $t_{B/D}$ can be obtained from detailed tables of the t distribution prepared by Dunn (1961), or can be computed with Equation 21.27 (which is described in Keppel (1991)).

$$t_{B/D} = z + \frac{z^3 + z}{4(df_{WG} - 2)} \quad (\text{Equation 21.27})$$

The value of z in Equation 21.27 is derived from **Table A1 (Table of the Normal Distribution)** in the **Appendix**. It is the z value above which $\alpha_{PC/2}$ of the cases in the normal distribution falls. Since in our example $\alpha_{PC} = .0167$, we look up the z value above which $.0167/2 = .0083$ of the distribution falls.³⁴ From **Table A1** we can determine that the z value which corresponds to the proportion .0083 is $z = 2.39$. Substituting $z = 2.39$ in Equation 21.27, the value $t_{B/D} = 2.79$ is computed.

$$t_{B/D} = 2.39 + \frac{(2.39)^3 + 2.39}{4(12 - 2)} = 2.79$$

Substituting the value $t_{B/D} = 2.79$ in Equation 21.26, the value $CD_{B/D} = 2.43$ is computed.

$$CD_{B/D} = 2.79 \sqrt{\frac{(2)(1.9)}{5}} = 2.43$$

Thus, in order to be significant, the difference between any pair of means contrasted in a simple comparison must be at least 2.43 units. Referring to **Table 21.5**, we can determine that (as is the case with **multiple t tests/Fisher's LSD test**) the following comparisons are significant: Group 1 versus Group 2; Group 1 versus Group 3 (since the difference between the means of the aforementioned groups is larger than $CD_{B/D} = 2.43$). Note that the value $CD_{B/D} = 2.43$ is larger than the value $CD_{LSD} = 1.90$, computed with Equation 21.24. The difference between the two CD values reflects the fact that in the case of the **Bonferroni–Dunn test**, for the set of $c = 3$ simple comparisons the value of α_{FW} is .05, whereas in the case of **multiple t tests/Fisher's LSD test**, the value of α_{FW} (which is computed with Equation 21.13) is .14. By virtue of adjusting the value of α_{FW} , the **Bonferroni–Dunn test** will always result in a larger CD value than the value computed with **multiple t tests/Fisher's LSD test**.³⁵

The **Bonferroni–Dunn test** can be used for both simple and complex comparisons. Earlier in this section, it was noted that both simple and complex comparisons involving two sets of means (where each set of means in a complex comparison consists of a single mean or a combination of means) represent single degree of freedom comparisons. Keppel (1991, p. 167) notes that the number of possible single degree of freedom comparisons (to be designated $c_{(1 \text{ df})}$) in a set of data can be computed with Equation 21.28.

$$c_{(1 \text{ df})} = 1 + \frac{(3^k - 1)}{2} - 2^k \quad (\text{Equation 21.28})$$

Employing Equation 21.28 with Example 21.1 (where $k = 3$), the value $c_{(1 \text{ df})} = 6$ is computed.

$$c_{(1 \text{ df})} = 1 + \frac{(3^3 - 1)}{2} - 2^3 = 6$$

The $c_{(1\ df)} = 6$ possible single degree of freedom comparisons that are possible when $k = 3$ follow: Group 1 versus Group 2; Group 1 versus Group 3; Group 2 versus Group 3; Group 1 versus Groups 2 and 3; Group 2 versus Groups 1 and 3; Group 3 versus Groups 1 and 2. Thus, if the **Bonferroni–Dunn test** is employed to conduct all six possible single degree of freedom comparisons with $\alpha_{FW} = .05$, the per comparison error rate will be $\alpha_{PC} = .05/6 = .0083$. Since $\alpha_{PC}/2 = .0083/2 = .00415$, employing **Table A1** we can determine the z value above which .00415 proportion of cases falls is approximately 2.635. Substituting $z = 2.635$ in Equation 21.27, the value $t_{B/D} = 3.16$ is computed.

$$t_{B/D} = 2.635 + \frac{(2.635)^3 + 2.635}{4(12 - 2)} = 3.16$$

Substituting $t_{B/D} = 3.16$ in Equation 21.26, the value $C_{B/D} = 2.75$ is computed.

$$C_{B/D} = 3.16 \sqrt{\frac{(2)(1.9)}{5}} = 2.75$$

Since Equation 21.26 is only valid for a simple comparison, the value $C_{B/D} = 2.75$ only applies to the three simple comparisons that are possible within the full set of six single degree of freedom comparisons. Thus, in order to be significant, the difference between any two means contrasted in a simple comparison must be at least 2.75 units. Note that the latter value is larger than $CD_{B/D} = 2.43$ computed for a set of $c = 3$ comparisons.

If one or more complex comparisons are conducted, the $t_{B/D}$ value a researcher employs will depend on the total number of comparisons (both simple and complex) being conducted. As is the case with **multiple t tests/Fisher's LSD test**, the computed value of $CD_{B/D}$ will also be a function of the coefficients employed in a comparison. Equation 21.29 is a generic equation that can be employed for both simple and complex comparisons to compute the value of $CD_{B/D}$. In the case of a simple comparison the term $\sum c_j^2 = 2$, thus resulting in Equation 21.26.

$$CD_{B/D} = t_{B/D} \sqrt{\frac{(\sum c_j^2)(MS_{WG})}{n}} \quad \text{(Equation 21.29)}$$

Equation 21.29 will be employed for the complex comparison of Group 3 versus the combined performance of Groups 1 and 2. On the assumption that the six possible single degree of freedom comparisons are conducted, the value $t_{B/D} = 3.16$ will be employed in the equation.

$$t_{B/D} = 3.16 \sqrt{\frac{(1.5)(1.9)}{5}} = 2.39$$

Thus, in order to be significant, the absolute value of the difference $\bar{X}_3 - [(\bar{X}_1 + \bar{X}_2)/2]$ must be at least 2.39 units. Since the obtained absolute difference of 1.7 is less than the latter value, the nondirectional alternative hypothesis $H_1: \mu_3 \neq (\mu_1 + \mu_2)/2$ is not supported. Recollect that when **multiple t tests/Fisher's LSD test** are employed for the same comparison, the latter alternative hypothesis is supported. The difference between the results of the two comparison procedures illustrates that the **Bonferroni–Dunn test** is a more conservative/less powerful procedure.

It should be noted that in conducting comparisons (especially if they are planned) a researcher may not elect to conduct all possible comparisons between pairs of means. Obviously,

the fewer comparisons that are conducted, the higher the value for α_{PC} that can be employed for the **Bonferroni–Dunn test**. Nevertheless, some researchers consider the **Bonferroni–Dunn** adjustment to be too severe, regardless of how many comparisons are conducted. In view of this, various sources (e.g., Howell (1992, 1997) and Keppel (1991)) describe a modified version of the **Bonferroni–Dunn test** that can be employed if one believes that the procedure described in this section sacrifices too much power.

It should also be pointed out that in conducting the **Bonferroni–Dunn test**, as well as any other comparison procedures which result in a reduction of the value of α_{PC} , it is not necessary that each comparison be assigned the same α_{PC} value. As long as the sum of the α_{PC} values adds up to the value stipulated for α_{FW} , the α_{PC} values can be distributed in any way the researcher deems prudent. Thus, if certain comparisons are considered more important than others, the researcher may be willing to tolerate a higher α_{PC} rate for such comparisons. As an example, assume a researcher conducts three comparisons and sets $\alpha_{FW} = .05$. If the first of the comparisons is considered to be the one of most interest and the researcher wants to maximize the power of that comparison, the α_{PC} rate for that comparison can be set equal to .04, and the α_{PC} rate for each of the other two comparisons can be set at .005. Note that since the sum of the three values is .05, the value $\alpha_{FW} = .05$ is maintained.

Test 21c: Tukey’s HSD test (The term **HSD** is an abbreviation for **honestly significant difference**)³⁶ **Tukey’s HSD test** is generally recommended for unplanned comparisons when a researcher wants to make **all possible pairwise comparisons** (i.e., simple comparisons) in a set of data. The total number of pairwise comparisons (c) that can be conducted for a set of data can be computed with the following equation: $c = [k(k - 1)]/2$. Thus, if $k = 3$, the total number of possible pairwise comparisons is $c = [3(3 - 1)]/2 = 3 = 3$ (which in the case of Example 21.1 are Group 1 versus Group 2, Group 1 versus Group 3, and Group 2 versus Group 3).

Tukey’s HSD test (Tukey, 1953) controls the **familywise Type I error rate** so that it will not exceed the prespecified alpha value employed in the analysis. Many sources view it as a good compromise among the available unplanned comparison procedures, in that it maintains an acceptable level for α_{FW} , without resulting in an excessive decrease in power.³⁷ **Tukey’s HSD test** is one of a number of comparison procedures that are based on the **Studentized range statistic** (which is represented by the notation q). Like the t distribution, the distribution for the **Studentized range statistic** is also employed to compare pairs of means. When the total number of groups/treatments involved in an experiment is greater than two, a tabled critical q value will be higher than the corresponding tabled critical t value for **multiple t tests/Fisher’s LSD test** for the same comparison.³⁸ For a given degrees of freedom value, the magnitude of a tabled critical q value increases as the number of groups employed in an experiment increase. **Table A13** in the **Appendix** (which is discussed in more detail later in this section) is the **Table of the Studentized Range Statistic**.

Equation 21.30 is employed to compute the q statistic, which represents the test statistic for **Tukey’s HSD test**.

$$q = \frac{\bar{X}_a - \bar{X}_b}{\sqrt{\frac{MS_{WG}}{n}}} \quad (\text{Equation 21.30})$$

Equation 21.30 will be employed with Example 21.1 to conduct the simple comparison of Group 1 versus Group 2. When the latter comparison is evaluated with Equation 21.30, the value $q = 4.22$ is computed.

$$q = \frac{9.2 - 6.6}{\sqrt{\frac{1.9}{5}}} = 4.22$$

The obtained value $q = 4.22$ is evaluated with [Table A13](#). The latter table contains the two-tailed .05 and .01 critical q values that are employed to evaluate a nondirectional alternative hypothesis at the .05 and .01 levels, or a directional alternative hypothesis at the .10 and .02 levels. (It should be noted that Kirk (1995, p. 144) states that the **Tukey procedure** and all other unplanned comparison procedures should only be employed to evaluate a nondirectional alternative hypothesis.) As is the case with previous comparisons, the analysis will be in reference to the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$, with $\alpha_{FW} = .05$. Employing the section of [Table A13](#) for the .05 critical values, we locate the q value that is in the cell which is the intersection of the column for $k = 3$ means (which represents the total number of groups upon which the omnibus F value is based) and the row for $df_{\text{error}} = 12$ (which represents the value $df_{WG} = df_{\text{error}} = 12$ computed for the omnibus F test). The tabled critical $q_{.05}$ value for $k = 3$ means and $df_{\text{error}} = 12$ is $q_{.05} = 3.77$. In order to reject the null hypothesis, the obtained absolute value of q must be equal to or greater than the tabled critical value at the prespecified level of significance.³⁹ Since the obtained value $q = 4.22$ is greater than the tabled critical two-tailed value $q_{.05} = 3.77$, the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is supported at the .05 level (where .05 represents the value of α_{FW}). It is not supported at the .01 level, since $q = 4.22$ is less than the tabled critical value $q_{.01} = 5.05$.

Equation 21.31, which is algebraically derived from Equation 21.30, can be employed to compute the minimum required difference (CD_{HSD}) in order for two means to differ significantly from one another at a prespecified level of significance.⁴⁰

$$CD_{\text{HSD}} = q_{(k, df_{WG})} \sqrt{\frac{MS_{WG}}{n}} \quad (\text{Equation 21.31})$$

Where: $q_{(k, df_{WG})}$ is the tabled critical q value for k groups/means and df_{WG} is the value employed for the omnibus F test

Employing the appropriate values in Equation 21.31, the value $CD_{\text{HSD}} = 2.32$ is computed.

$$CD_{\text{HSD}} = (3.77) \sqrt{\frac{1.9}{5}} = 2.32$$

Thus, in order to be significant, the difference $\bar{X}_1 - \bar{X}_2$ must be at least 2.32 units. Note that the value $CD_{\text{HSD}} = 2.32$ is greater than $CD_{\text{LSD}} = 1.90$, but less than $CD_{\text{B/D}} = 2.43$. This reflects the fact that in conducting all pairwise comparisons, **Tukey's HSD test** will provide a more powerful test of an alternative hypothesis than the **Bonferroni-Dunn test**. It also indicates that **Tukey's HSD test** is less powerful than **multiple t tests/Fisher's LSD test** (which does not control the value of α_{FW}).

The use of Equations 21.30 and 21.31 for **Tukey's HSD test** is based on the following assumptions: a) The distribution of data in the underlying population from which each of the samples is derived is normal; b) The variances of the k underlying populations represented by the k samples are equal to one another (i.e. homogeneous); and c) The sample sizes of each of the groups being compared are equal. Kirk (1982, 1995), among others, discusses a number of modifications of **Tukey's HSD test** which are recommended when there is reason to believe that all or some of the aforementioned assumptions are violated.⁴¹

Test 21d: The Newman–Keuls test The **Newman–Keuls test** (Keuls (1952), Newman (1939)) is another procedure for pairwise unplanned comparisons that employs the **Studentized range statistic**. Although the **Newman–Keuls test** is more powerful than **Tukey’s HSD test**, unlike the latter test it does not insure that in a set of pairwise comparisons the **familywise Type I error rate** will not exceed a prespecified alpha value. Equations 21.30 and 21.31 (which are employed for **Tukey’s HSD test**) are also employed for the **Newman–Keuls test**. When, however, the latter equations are used for the **Newman–Keuls test**, the appropriate tabled critical q value will be a function of how far apart the two means being compared are from one another.

To be more specific, the k means are arranged ordinally (i.e., from lowest to highest). Thus, in the case of Example 21.1, the $k = 3$ means are arranged in the following order:

$$\bar{X}_3 = 6.2 \quad \bar{X}_2 = 6.6 \quad \bar{X}_1 = 9.2$$

For each pairwise comparison that can be conducted, the number of **steps** between the two means involved is determined. Because of the fact that the tabled critical q value is a function of the number of steps or **layers** that separate two mean values, the **Newman–Keuls test** is often referred to as a **stepwise** or **layered test**. The number of steps (which will be represented by the notation s) between any two means is determined as follows: Starting with the lower of the two mean values (which will be the mean to the left), count until the higher of the two mean values is reached. Each mean value employed in counting from the lower to the higher value in the pair represents one step. Thus, $s = 2$ steps are involved in the simple comparison of Group 1 versus Group 2, since we start at the left with $\bar{X}_2 = 6.6$ (the lower of the two means involved in the comparison) which is step 1, and move right to the adjacent value $\bar{X}_1 = 9.2$ (the higher of the two means involved in the comparison), which represents step 2. If Group 1 and Group 3 are compared, $s = 3$ steps separate the two means, since we start at the left with $\bar{X}_3 = 6.2$ (the lower of the two means involved in the comparison), move to the right counting $\bar{X}_2 = 6.6$ as step 2, and then move to $\bar{X}_1 = 9.2$ (the higher of the two means involved in the comparison), which is step 3.

The **Newman–Keuls test** protocol requires that the pairwise comparisons be conducted in a specific order. The first comparison conducted is between the two means which are separated by the largest number of steps (which will represent the largest absolute difference between any two means). If the latter comparison is significant, any comparisons involving the second largest number of steps are conducted. If all the comparisons in the latter subset of comparisons are significant, the subset of comparisons for the next largest number of steps is conducted, and so on. The basic rule upon which the protocol is based is that if at any point in the analysis a comparison fails to yield a significant result, no further comparisons are conducted on pairs of means that are separated by fewer steps than the number of steps involved in the nonsignificant comparison. Employing this protocol with Example 21.1, the first comparison that is conducted is \bar{X}_1 versus \bar{X}_3 , which involves $s = 3$ steps. If that comparison is significant, the comparisons \bar{X}_1 versus \bar{X}_2 and \bar{X}_2 versus \bar{X}_3 , both of which involve $s = 2$ steps, are conducted.

In employing **Table A13** to determine the tabled critical q value to employ with Equations 21.30 and 21.31, instead of employing the column for k (the total number of groups/means in the set of data), the column that is used is the one that corresponds to the number of steps between the two means involved in a comparison. Thus, if Group 1 and Group 3 are compared, the column for $k = 3$ groups in **Table A13** is employed in determining the value of q . Since the value of df_{error} remains $df_{\text{WG}} = 12$, the value $q_{.05} = 3.77$ is employed in Equation 21.31. Since the latter value is identical to the q value employed for **Tukey’s HSD test**, the **Newman–Keuls** value computed for the minimum required difference for two means ($CD_{N/K}$) will be the same as the value CD_{HSD} computed for **Tukey’s HSD test**.⁴² Thus, $CD_{N/K} = (3.77)\sqrt{1.9/5} = 2.32$. The

latter result indicates that if $\alpha = .05$, the minimum required difference between two means for the comparison Group 1 versus Group 3 is $CD_{N/K} = 2.32$.⁴³ Since the absolute difference $|\bar{X}_1 - \bar{X}_3| = 3$ is greater than $CD_{N/K} = 2.32$, the comparison is significant.

Since the result of the $s = 3$ step comparison is significant, the **Newman-Keuls test** is employed to compare Group 1 versus Group 2 and Group 2 versus Group 3, which represent $s = 2$ step comparisons. The value $q_{.05} = 3.08$ is employed in Equation 21.31, since the latter value is the tabled critical $q_{.05}$ value for $k = 2$ means and $df_{\text{error}} = 12$. Substituting $q_{.05} = 3.08$ in Equation 21.31 yields the value $CD_{N/K} = (3.08)\sqrt{1.9/5} = 1.90$. Since the absolute difference $|\bar{X}_1 - \bar{X}_2| = 2.6$ is greater than $CD_{N/K} = 1.90$, there is a significant difference between the means of Groups 1 and 2. Since the absolute difference $|\bar{X}_2 - \bar{X}_3| = .4$ is less than $CD_{N/K} = 1.90$, the researcher cannot conclude there is a significant difference between the means of Groups 2 and 3. Note that the value $CD_{N/K} = 1.90$ computed for a two-step analysis is smaller than the value $CD_{N/K} = 2.32$ computed for the three-step analysis. The general rule is that the fewer the number of steps, the smaller the computed $CD_{N/K}$ value.

The astute reader will observe that $CD_{N/K} = 1.90$ is identical to $CD_{LSD} = 1.90$ obtained with Equation 21.24. The latter result illustrates that when two steps are involved in a **Newman-Keuls** comparison, it will always yield a value that is identical to CD_{LSD} (i.e., the value computed with **multiple t tests/Fisher's LSD test**). In point of fact, when $s = 2$, for a given degrees of freedom value, the relationship between the values of q and t is as follows: $q = t\sqrt{2}$ and $t = q/\sqrt{2}$. If the value $q_{.05} = 3.08$ is employed in the equation $t = q/\sqrt{2}$, $t = (3.08)/\sqrt{2} = 2.18$. Note that $(t_{.05} = 2.18)^2 = (F_{.05} = 4.75)$, and that $F_{.05} = 4.75$ is the tabled critical value employed in Equation 21.24 which yields the value $CD_{LSD} = 1.90$.

The value of α_{FW} associated with the **Newman-Keuls test** will be higher than the value of α_{FW} for **Tukey's HSD test**. This is a direct result of the fact that the tabled critical **Studentized range** values employed for the **Newman-Keuls test** are smaller than those employed for **Tukey's HSD test** (with the exception of the comparison contrasting the lowest and highest means in the set of k means). Within any subset of comparisons which are an equal number of steps apart from one another, the overall Type I error rate for the **Newman-Keuls test** within that subset will not exceed the prespecified value of alpha. The latter, however, does not insure that α_{FW} for all the possible pairwise comparisons will not exceed the prespecified value of alpha. Because of its higher α_{FW} rate, the **Newman-Keuls test** is generally not held in high esteem as an unplanned comparison procedure. Excellent discussions of the **Newman-Keuls test** can be found in Maxwell and Delaney (1990) and Howell (1992, 1997).

Test 21e: The Scheffé test The **Scheffé test** (Scheffé, 1953), which is employed for unplanned comparisons, is commonly described as the most conservative of the unplanned comparison procedures. The test maintains a fixed value for α_{FW} , regardless of how many simple and complex comparisons are conducted. By virtue of controlling for a large number of potential comparisons, the error rate for any single comparison (i.e., α_{PC}) will be lower than the error rate associated with any of the other comparison procedures (assuming an alternative procedure employs the same value for α_{FW}).⁴⁴ Since in conducting unplanned pairwise comparisons **Tukey's HSD test** provides a more powerful test of an alternative hypothesis than the **Scheffé test**, most sources note that it is not prudent to employ the **Scheffé test** if only simple comparisons are being conducted. The **Scheffé test** is, however, recommended whenever a researcher wants to maintain a specific α_{FW} level, regardless of how many simple and complex comparisons are conducted. Sources note that the **Scheffé test** can accommodate unequal sample sizes and is quite robust with respect to violations of the assumptions underlying the analysis of variance (i.e., homogeneity of variance and normality of the underlying population distributions). Because of the low value the **Scheffé test** imposes on the value of α_{PC} and the consequent loss of power

associated with each comparison, some sources recommend that in using the test a researcher employ a larger value for α_{FW} than would ordinarily be the case. Thus, one might employ $\alpha_{FW} = .10$ for the **Scheffé test**, instead of $\alpha_{FW} = .05$ which might be employed for a less conservative comparison procedure.

Equation 21.32 is employed to compute the minimum required difference for the **Scheffé test** (CD_S) in order for two means to differ significantly from one another at a prespecified level of significance. Whereas Equation 21.32 only applies to simple comparisons, Equation 21.33 is a generic equation that can be employed for both simple and complex comparisons.

$$CD_S = \sqrt{(k - 1)(F_{(df_{BG}, df_{WG})})} \sqrt{\frac{2MS_{WG}}{n}} \quad (\text{Equation 21.32})$$

$$CD_S = \sqrt{(k - 1)(F_{(df_{BG}, df_{WG})})} \sqrt{\frac{(\sum c_j^2)(MS_{WG})}{n}} \quad (\text{Equation 21.33})$$

In Equations 21.32 and 21.33, the value $F_{(df_{BG}, df_{WG})}$ is the tabled critical value that is employed for the omnibus F test for a value of alpha that corresponds to the value of α_{FW} . Thus, in Example 21.1, if $\alpha_{FW} = .05$, $F_{.05} = 3.89$ for $df = 2, 12$ is used in Equations 21.32/21.33. Employing Equation 21.32, the value $CD_S = 2.43$ is computed for the simple comparison of Group 1 versus Group 2.

$$CD_S = \sqrt{(3 - 1)(3.89)} \sqrt{\frac{(2)(1.9)}{5}} = 2.43$$

Thus, in order to be significant, the difference $\bar{X}_1 - \bar{X}_2$ (as well as the difference between the means of any other two groups) must be at least 2.43 units. Since the absolute difference $|\bar{X}_1 - \bar{X}_2| = 2.6$ is greater than $CD_S = 2.43$, the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is supported. Note that for the same comparison, the CD value computed for the **Scheffé test** is larger than the previously computed values $CD_{LSD} = CD_{N/K} = 1.90$ and $CD_{HSD} = 2.32$, but is equivalent to $CD_{B/D} = 2.43$. The fact that $CD_S = CD_{B/D}$ for the comparison under discussion illustrates that although for simple comparisons the **Scheffé test** is commonly described as the most conservative of the unplanned comparison procedures, when the **Bonferroni–Dunn test** is employed for simple comparisons it may be as or more conservative than the **Scheffé test**. Maxwell and Delaney (1990) note that in instances where a researcher conducts a small number of comparisons, the **Bonferroni–Dunn test** will provide a more powerful test of an alternative hypothesis than the **Scheffé test**. However, as the number of comparisons increase, at some point the **Scheffé test** will become more powerful than the **Bonferroni–Dunn test**. In general (although there are some exceptions), the **Bonferroni–Dunn test** will be more powerful than the **Scheffé test** when the number of comparisons conducted is less than $[k(k - 1)]/2$.

The **Scheffé test** is most commonly recommended when at least one complex comparison is conducted in a set of unplanned comparisons. Although the other comparison procedures discussed in this section can be employed for unplanned complex comparisons, the **Scheffé test** is viewed as a more desirable alternative by most sources. It will now be demonstrated how the **Scheffé test** can be employed for the complex comparison \bar{X}_3 versus $(\bar{X}_1 + \bar{X}_2)/2$. Substituting the value $\sum c_j^2 = 1.5$ (which is computed in Table 21.4) and the other relevant values in Equation 21.33, the value $CD_S = 2.11$ is computed.

$$CD_S = \sqrt{(3 - 1)(3.89)} \sqrt{\frac{(1.5)(1.9)}{5}} = 2.11$$

Thus, in order to be significant, the difference $\bar{X}_3 - [(\bar{X}_1 + \bar{X}_2)/2]$ (as well as the difference between any set of means in a complex comparison for which $\sum c_j^2 = 1.5$) must be equal to or greater than 2.11 units. Since the absolute difference $|\bar{X}_3 - [(\bar{X}_1 + \bar{X}_2)/2]| = 1.7$ is less than $CD_S = 2.11$, the nondirectional alternative hypothesis $H_1: \mu_3 \neq (\mu_1 + \mu_2)/2$ is not supported. Note that the CD value computed for the **Scheffé test** is larger than the previously computed value $CD_{LSD} = 1.65$, but less than $CD_{B/D} = 2.39$ computed for the same complex comparison. This reflects the fact that for the complex comparison \bar{X}_3 versus $(\bar{X}_1 + \bar{X}_2)/2$, the **Scheffé test** is not as powerful as **multiple t tests/Fisher's LSD test**, but is more powerful than the **Bonferroni–Dunn test**.⁴⁵

Equation 21.34 can also be employed for the **Scheffé test** for both simple and complex comparisons.

$$F_S = (k - 1)F_{(BG, WG)} \quad \text{(Equation 21.34)}$$

Where: $F_{(BG, WG)}$ is the tabled critical value at the prespecified level of significance employed in the omnibus F test

In order to use Equation 21.34 it is necessary to first employ Equations 21.17–21.19 to compute the value of F_{comp} for the comparison being conducted. The value computed for F_{comp} will serve as the test statistic for the **Scheffé test**. Earlier in this section (under the discussion of **linear contrasts**) the value $F_{\text{comp}} = 5.07$ is computed for the complex comparison \bar{X}_3 versus $(\bar{X}_1 + \bar{X}_2)/2$. When F_{comp} is used as the test statistic for the **Scheffé test**, the critical value employed to evaluate it is different than the critical value employed in evaluating a **linear contrast**. Equation 21.34 is used to determine the **Scheffé test** critical value. In order for a comparison to be significant, the computed value of F_{comp} must be equal to or greater than the critical F value computed with Equation 21.34 (which is represented by the notation F_S). In employing Equation 21.34 to compute F_S , the tabled critical value employed for the omnibus F test (which in the case of Example 21.1 is $F_{.05} = 3.89$) is multiplied by $(k - 1)$. Obviously, the resulting value will be higher than the tabled critical value employed for the **linear contrast** for the same comparison. When the appropriate values for Example 21.1 are substituted in Equation 21.34, the value $F_S = 7.78$ is computed.

$$F_S = (3 - 1)(3.89) = 7.78$$

Since the computed value $F_{\text{comp}} = 5.07$ is less than the critical value $F_S = 7.78$ computed with Equation 21.34, it indicates that the nondirectional alternative hypothesis $H_1: \mu_3 \neq (\mu_1 + \mu_2)/2$ is not supported. Note that the value $F_S = 7.78$ is larger than the value $F_{.05} = 4.75$ (which is the tabled critical value for $df_{\text{num}} = 1$ and $df_{\text{den}} = df_{WG} = 12$) that is employed for the linear contrast for the same comparison. Recollect that the alternative hypothesis $H_1: \mu_3 \neq (\mu_1 + \mu_2)/2$ is supported when a **linear contrast** is conducted.

In closing the discussion of the **Scheffé test** some general comments will be made regarding the value of α_{FW} for the **Scheffé test**, the **Bonferroni–Dunn test**, and **Tukey's HSD test**. In the discussion to follow it will be assumed that upon computation of an omnibus F value, a researcher wishes to conduct a series of unplanned comparisons for which the **familywise error rate** does not exceed $\alpha_{FW} = .05$.⁴⁶

a) If all possible comparisons (simple and complex) are conducted with the **Scheffé test**, the

value of α_{FW} will equal exactly .05. When $k \geq 3$ there are actually an infinite number of comparisons that can be made (Maxwell and Delaney (1990, p. 190)). To illustrate this, assume $k = 3$. Beside the three pairwise/simple comparisons (Group 1 versus Group 2; Group 1 versus Group 3; Group 2 versus Group 3) and the three apparent complex comparisons (The average of Groups 1 and 2 versus Group 3; The average of Groups 1 and 3 versus Group 2; The average of Groups 2 and 3 versus Group 1), in the case of a complex comparison it is possible to combine two groups so that one group contributes more to the composite mean representing the two groups than does the other group. As an example, in comparing Groups 1 and 2 with Group 3, a coefficient of 7/8 can be assigned to Group 1 and a coefficient of 1/8 to Group 2. Employing these coefficients, a composite mean value can be computed to represent the mean of the two groups which is contrasted with Group 3. It should be obvious that if one can stipulate any combination of two coefficients/weights that add up to 1, there are potentially an infinite number of coefficient combinations that can be assigned to any two groups, and therefore an infinite number of possible comparisons can result from coefficient combinations involving the comparison of two groups with a third group. If fewer than all possible comparisons are conducted with the **Scheffé test**, the value of α_{FW} will be less than .05, thus making it an overly conservative test (since the value of α_{PC} will be lower than is necessary for α_{FW} to equal .05).

b) If all possible comparisons are conducted employing the **Bonferroni–Dunn test**, the value of α_{FW} will be less than .05. As noted earlier, as the number of comparisons conducted increases, at some point the value of α_{FW} for the **Bonferroni–Dunn test** will be less than α_{FW} for the **Scheffé test**, and thus at that point the **Bonferroni–Dunn test** will be even more conservative (and thus less powerful) than the **Scheffé test**. The decrease in the value of α_{FW} for the **Bonferroni–Dunn test** results from the fact that within the set of comparisons conducted, not all comparisons will be orthogonal with one another. Winer *et al.* (1991) note that when comparisons conducted with the **Bonferroni–Dunn test** are orthogonal, the following is true: $\alpha_{FW} = c(\alpha_{PC})$. However, when some of the comparisons conducted are not orthogonal, $\alpha_{FW} < c(\alpha_{PC})$. Thus, by virtue of some of the comparisons being nonorthogonal, the **Bonferroni–Dunn test** becomes a more conservative test (i.e., $\alpha_{FW} < .05$).

c) If **Tukey’s HSD test** is employed for conducting all possible pairwise comparisons, the value of α_{FW} will be exactly .05, even though the full set of pairwise comparisons will not constitute an orthogonal set. As noted above, if the **Bonferroni–Dunn test** is employed for the full set of pairwise comparisons, due to the presence of nonorthogonal comparisons, the value of α_{FW} will be less than .05, and thus the value of $CD_{B/D}$ will be larger than the value of CD_{HSD} . If in addition to conducting all pairwise comparisons with **Tukey’s HSD test**, complex comparisons are also conducted, the value of α_{FW} will exceed .05. As the number of complex comparisons conducted increases, the value of α_{FW} increases. When complex comparisons are conducted, **Tukey’s HSD test** is not as powerful as the **Scheffé test**.

Test 21f: The Dunnett test The **Dunnett test** (1955, 1964) is a comparison procedure, only employed for simple comparisons, that is designed to compare a control group with the other $(k - 1)$ groups in a set of data. Under such conditions the **Dunnett test** provides a more powerful test of an alternative hypothesis than do the **Bonferroni–Dunn test**, **Tukey’s HSD test**, and the **Scheffé test**. This is the case, since for the same value of α_{FW} , the α_{PC} value associated with the **Dunnett test** will be higher than the α_{PC} values associated with the aforementioned procedures (and, by virtue of this, provides a more powerful test of an alternative hypothesis). The larger α_{PC} value for the **Dunnett test** is predicated on the fact that by virtue of limiting the comparisons to contrasting a control group with the other groups, the **Dunnett test** statistic is based on the assumption that fewer comparisons are conducted than will be the case if all pairwise comparisons are conducted. Consequently, if a researcher specifies that $\alpha_{FW} = .05$, and the mean

of the control group is contrasted with the means of each of the other $(k - 1)$ groups, the **Dunnett test** insures that the **familywise Type I error rate** will not exceed .05. It should be noted that since the control group is involved in each of the comparisons that are conducted, the comparisons will not be orthogonal to one another. In illustrating the computation of the **Dunnett test** statistic, we will assume that in Example 21.1 Group 1 (the group that is not exposed to noise) is a control group, and that Groups 2 and 3 (both of which are exposed to noise) are experimental groups. Thus, employing the **Dunnett test**, the following two comparisons will be conducted with $\alpha_{FW} = .05$: Group 1 versus Group 2; Group 1 versus Group 3.

The test statistic for the **Dunnett test** (t_D) is computed with Equation 21.35, which, except for the fact that a t_D value is computed, is identical to Equation 21.22 (which is employed to compute the test statistic for **multiple t tests/Fisher's LSD test**).⁴⁷

$$t_D = \frac{\bar{X}_a - \bar{X}_b}{\sqrt{\frac{2MS_{WG}}{n}}} \quad \text{(Equation 21.35)}$$

Equation 21.35 is employed below to compute the value $t_D = 2.99$ for the simple comparison of Group 1 versus Group 2.

$$t_D = \frac{9.2 - 6.6}{\sqrt{\frac{(2)(1.9)}{5}}} = 2.99$$

The computed value $t_D = 2.99$ is evaluated with **Table A14 (Table of Dunnett's Modified t Statistic for a Control Group Comparison)** in the **Appendix**. The latter table, which contains both two-tailed and one-tailed .05 and .01 critical values, is based on a modified t distribution derived by Dunnett (1955, 1964). Dunnett (1955) computed one-tailed critical values, since in comparing one or more treatments with a control group a researcher is often interested in the direction of the difference. The tabled critical t_D values are listed in reference to k , the total number of groups/treatments employed in the experiment, and the value of $df_{\text{error}} = df_{WG}$ computed for the omnibus F test.

For $k = 3$ and $df_{\text{error}} = df_{WG} = 12$, the tabled critical two-tailed .05 and .01 values are $t_{D,.05} = 2.50$ and $t_{D,.01} = 3.39$, and the tabled critical one-tailed .05 and .01 values are $t_{D,.05} = 2.11$ and $t_{D,.01} = 3.01$. The computed value $t_D = 2.99$ is greater than the tabled critical two-tailed and one-tailed .05 t_D values but less than the tabled critical two-tailed and one-tailed .01 t_D values. Thus, for $\alpha_{FW} = .05$ (but not $\alpha_{FW} = .01$), the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ and the directional alternative hypothesis $H_1: \mu_1 > \mu_2$ are supported. The second comparison involving the control group (Group 1) versus Group 3, yields the value $t_D = (9.2 - 6.2)/\sqrt{[(2)(1.9)]/5} = 3.45$. Since the value $t_D = 3.45$ is greater than the tabled critical two-tailed and one-tailed .05 and .01 t_D values, the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_3$ and the directional alternative hypothesis $H_1: \mu_1 > \mu_3$ are supported for both $\alpha_{FW} = .05$ and $\alpha_{FW} = .01$.

Equation 21.36 is employed to compute the minimum required difference for the **Dunnett test** (designated CD_D) in order for two means to differ significantly from one another at a pre-specified level of significance.

$$CD_D = t_{D,(k, df_{WG})} \sqrt{\frac{2MS_{WG}}{n}} \quad \text{(Equation 21.36)}$$

Where: $t_{D_{(k, df_{WG})}}$ is the tabled critical value for **Dunnett's modified t statistic** for k groups and df_{WG} at the prespecified value of α_{FW}

In employing Equation 21.36, $\alpha_{FW} = .05$ will be employed, and it will be assumed that a nondirectional alternative hypothesis is evaluated for both comparisons. Substituting the two-tailed .05 value $t_{D_{.05}} = 2.50$ in Equation 21.36, the value $CD_D = 2.18$ is computed.

$$CD_D = 2.50 \sqrt{\frac{2(1.9)}{5}} = 2.18$$

Thus, in order to be significant, the differences $\bar{X}_1 - \bar{X}_2$ and $\bar{X}_1 - \bar{X}_3$ must be at least 2.18 units. Since the absolute differences $|\bar{X}_1 - \bar{X}_2| = 2.6$ and $|\bar{X}_1 - \bar{X}_3| = 3$ are greater than $CD_D = 2.18$, the nondirectional alternative hypothesis is supported for both comparisons. Note that $CD_D = 2.18$ computed for the **Dunnett test** is larger than $CD_{LSD} = 1.90$ computed for **multiple t tests/Fisher's LSD test** (for a simple comparison), but is less than the CD values computed for a simple comparison for the **Bonferroni–Dunn test** ($CD_{B/D} = 2.43$), **Tukey's HSD test** ($CD_{HSD} = 2.32$), and the **Scheffé test** ($CD_S = 2.43$).

Additional discussion of comparison procedures and final recommendations The accuracy of the comparison procedures described in this section may be compromised if the homogeneity of variance assumption underlying the analysis of variance (the evaluation of which is described later in Section VI) is violated. This is the case, since in such an instance MS_{WG} may not provide the best measure of error variability for a given comparison. Violation of the homogeneity of variance assumption can either increase or decrease the Type I error rate associated with a comparison, depending upon whether MS_{WG} overestimates or underestimates the pooled variability of the groups involved in a specific comparison. It is also the case that when the homogeneity of variance assumption is violated, the accuracy of a comparison may be even further compromised when there is not an equal number of subjects in each group. Sources that discuss these general issues (e.g., Howell (1992, 1997), Kirk (1982, 1995), Maxwell and Delaney (1990), Winer *et al.* (1991)) provide alternative equations which are recommended when the homogeneity of variance assumption is violated and/or sample sizes are unequal.

As a general rule, the measure of within-groups variability that is employed in equations which are recommended when there is heterogeneity of variance is based on the pooled within-groups variability of just those groups which are involved in a specific comparison. Since the latter measure has a smaller degrees of freedom associated with it than MS_{WG} , the tabled critical value for the analysis will be based on fewer degrees of freedom. Although the loss of degrees of freedom can reduce the power of the test, it may be offset if the revised measure of within-groups variability is less than MS_{WG} . A full discussion of the subject of violation of the homogeneity of variance assumption with comparisons is beyond the scope of this book. The reader who refers to sources that discuss the subject in greater detail will discover that there is a lack of agreement with respect to what procedure is most appropriate to employ when the assumption is violated.

Numerous other multiple comparison procedures have been developed in addition to those described in this section. Howell (1992, 1997) and Kirk (1995), among others, describe a number of alternative procedures. Howell (1997) describes a procedure developed by Ryan (1960), which is a compromise between **Tukey's HSD test** and the **Newman–Keuls test**. To be more specific, Ryan's (1960) procedure maintains the value of α_{FW} at the desired level, but at the same time allows the critical difference required between pairs of means to vary as a function of step size.

Kirk (1995, Ch. 4) describes the merits and limitations of 22 multiple comparison procedures. Within the framework of his discussion, Kirk (1995) notes that in conducting comparisons, a researcher's priority should be to guard against inflation of the Type I error rate, yet at the same time to employ a procedure that maximizes power (i.e., has a high likelihood of identifying a significant effect).

At this point the author will present some general recommendations regarding the use of comparison procedures for the analysis of variance.⁴⁸ From what has been said, it should be apparent that in conducting comparisons the minimum value required for two means to differ significantly from one another can vary dramatically, depending upon which comparison procedure a researcher employs. Although some recommendations have been made with respect to when it is viewed most prudent to employ each of the comparison procedures, in the final analysis the use of any of the procedures does not insure that a researcher will determine the truth regarding the relationship between the variables under study. Aside from the fact that researchers do not agree among themselves on which comparison procedure to employ (due largely to the fact that they do not concur with respect to the maximum acceptable value for α_{FW}), there is also the problem that one is not always able to assume with a high degree of confidence that all of the assumptions underlying a specific comparison procedure have, in fact, been met. In view of this, any probability value associated with a comparison may always be subject to challenge. Although most of the time a probability value may not be compromised to that great a degree, when one considers the fact that researchers may quibble over whether one should employ $\alpha_{FW} = .05$ versus $\alpha_{FW} = .10$, a minimal difference with respect to a probability value can mean a great deal, since it ultimately may determine whether a researcher elects to retain or reject a null hypothesis. If, in fact, the status of the null hypothesis is based on the result of a single study, it would seem that a researcher is obliged to arrive at a probability value in which he and others can have a high degree of confidence.⁴⁹

In view of everything that has been discussed, this writer believes that the general strategy for conducting comparisons suggested by Keppel (1991) is the most prudent to employ. Keppel (1991) suggests that in hypothesis testing involving **unplanned comparisons**, instead of just employing the two decision categories of **retaining the null hypothesis** versus **rejecting the null hypothesis**, a third category, **suspend judgement** be added. Specifically, Keppel (1991) recommends the following:

a) If the obtained difference between two means is less than the value of CD_{LSD} , **retain the null hypothesis**. Since the value of CD_{LSD} will be the smallest CD value computed with any of the available comparison procedures, it allows for the most powerful test of an alternative hypothesis.

b) If the obtained difference between two means is equal to or greater than the CD value associated with the comparison procedure which results in the **largest α_{FW} value** one is willing to tolerate, **reject the null hypothesis**. Based on the procedures described in this book (depending upon the number of comparisons that are conducted), the largest CD value will be generated through use of either the **Bonferroni–Dunn test** or the **Scheffé test**. However, the largest α_{FW} value a researcher may be willing to tolerate may be larger than the α_{FW} value associated with either of the aforementioned procedures. In such a case, the minimum CD value required to reject the null hypothesis will be smaller than $CD_{B/D}$ or CD_S .

c) If the obtained difference between two means is greater than or equal to CD_{LSD} , but less than the CD value associated with the largest α_{FW} value one is willing to tolerate, **suspend judgement**. It is recommended that one or more replication studies be conducted employing the relevant groups/treatments for any comparisons that fall in the **suspend judgement** category.

The above guidelines will now be applied to Example 21.1. Let us assume that three simple comparisons are conducted, and that the maximum **familywise Type I error rate** the researcher

is willing to tolerate is $\alpha_{FW} = .05$. Employing the above guidelines, the null hypothesis can be rejected for the comparisons of Group 1 versus Group 2 and Group 1 versus Group 3. This is the case, since $\bar{X}_1 - \bar{X}_2 = 2.6$ and $\bar{X}_1 - \bar{X}_3 = 3$, and in both instances the obtained difference between the means of the two groups is greater than $CD_{HSD} = 2.32$ (which insures that α_{FW} will not exceed .05). On the other hand, for the comparison of Group 2 versus Group 3, since the difference $\bar{X}_2 - \bar{X}_3 = .4$ is less than $CD_{LSD} = 1.90$ (which is the lowest of the computed CD values), the null hypothesis cannot be rejected. Thus, in the case of Example 21.1, none of the comparisons falls in the **suspend judgement** category. In point of fact, even if the α_{FW} value associated with the **Bonferroni–Dunn** and/or **Scheffé tests** is employed as the maximum acceptable α_{FW} rate, none of the comparisons falls in the **suspend judgement** category, since the absolute difference between the means for each comparison is either greater than or less than the relevant CD values.

As noted earlier, in the case of **planned comparisons** the issue of whether or not a researcher should control the value of α_{FW} is subject to debate. It can be argued that the strategy described for unplanned comparisons should also be employed with planned comparisons — with the stipulation that the largest value for α_{FW} that one is willing to tolerate for planned comparisons be higher than the value employed for unplanned comparisons. Nevertheless, one can omit the latter stipulation and argue that the same criterion be employed for both unplanned and planned comparisons. The rationale for the latter position is as follows. Assume that two researchers independently conduct the identical study. Researcher 1 has the foresight to plan c comparisons beforehand. Researcher 2, on the other hand, conducts the same set of c comparisons, but does not plan them beforehand. The truth regarding the populations involved in the comparisons is totally independent of who conducts the study. As a result of this, one can argue that the same criterion be applied, regardless of who conducts the investigation. If Researcher 1 is allowed to conduct a less conservative analysis (i.e., tolerate a higher α_{FW} rate) than Researcher 2, it is commensurate with giving Researcher 1 a bonus for having a bit more acumen than Researcher 2 (if we consider allowing one greater latitude with respect to rejecting the null hypothesis to constitute a bonus). It would seem that if, in the final analysis, the issue at hand is the truth concerning the populations under study, each of the two researchers should be expected to adhere to the same criterion, regardless of their expectations prior to conducting the study. If one accepts this line of reasoning, it would seem that the guidelines described in this section for unplanned comparisons should also be employed for planned comparisons.

In the final analysis, regardless of whether one has conducted planned or unplanned comparisons, when there is reasonable doubt in the mind of the researcher or there is reason to believe that there will be reasonable doubt among those who scrutinize the results of a study, it is always prudent to replicate a study. In other words, anytime the result of an analysis falls within the **suspend judgement** category (or perhaps even if the result is close to falling within it), a strong argument can be made for replicating a study. Thus, regardless of which comparison procedure one employs, if the result of a comparison is not significant, yet would have been had another comparison procedure been employed, it would seem logical to conduct at least one replication study in order to clarify the status of the null hypothesis. There is also the case where the result of a comparison turns out to be significant, yet would not have been with a more conservative comparison procedure. If in such an instance the researcher (or others who are familiar with the relevant literature) has reason to believe that a Type I error may have been committed, it would seem prudent to reevaluate the null hypothesis. In the final analysis, multiple replications of a result provide the most powerful evidence regarding the status of a null hypothesis. An effective tool that can be employed to pool the results of multiple studies which evaluate the same hypothesis is a methodology called **meta-analysis**, which is discussed in Section IX (the **Addendum**) of the **Pearson product-moment correlation coefficient (Test 28)**.

At this point in the discussion it is worth reiterating the difference between **statistical** and **practical significance** (which is discussed in both the **Introduction** and in Section VI of the ***t* test for two independent samples**). By virtue of employing a large sample size, virtually any test evaluating a difference between the means of two populations will turn out to be significant. This results from the fact that two population means are rarely identical. However, in most instances a minimal difference between two means is commensurate with there being no difference at all, since the magnitude of such a difference is of no practical or theoretical value. In conducting comparisons (or, for that matter, conducting any statistical test) one must decide what magnitude of difference is of practical and/or theoretical significance. To state it another way, one must determine the magnitude of the **effect size** one is attempting to identify.⁵⁰ If a researcher is able to stipulate a meaningful effect size prior to collecting the data for a study, he can design the study so that the test which is employed to evaluate the null hypothesis is sufficiently powerful to identify the desired effect size. As a general rule, a researcher is best able to control the power of a statistical test by employing a sample size that exceeds some minimal value. In the latter part of Section VI the computation of power for the **single-factor between-subjects analysis of variance** is discussed in reference to both the omnibus *F* test as well as for comparison procedures.

In the final analysis, when the magnitude of the obtained difference between the means involved in any comparison is deemed too small to be of practical or theoretical significance, it really becomes irrelevant whether a result is statistically significant. In such an instance if two or more comparison procedures yield conflicting results, replication of a study is not in order.

The computation of a confidence interval for a comparison The computation of a **confidence interval** provides a researcher with a mechanism for determining a range of values within which he can be confident the true difference between the means of two populations falls. Computation of a confidence interval for a comparison is a straightforward procedure which can be easily implemented following the computation of a *CD* value.⁵¹ Specifically, to compute the range of values that define the 95% confidence interval for any comparison, one should do the following: Add to and subtract the computed value of *CD* from the obtained difference between the two means involved in the comparison. As an example, let us assume **Tukey's HSD test** is employed to compute the value $CD_{HSD} = 2.32$ for the comparison involving Group 1 versus Group 2. To compute the 95% confidence interval, the value 2.32 is added to and subtracted from 2.6, which is the difference between the two means. Thus, $CI_{HSD, 95} = 2.6 \pm 2.32$, which can also be written as $.28 \leq (\mu_1 - \mu_2) \leq 4.92$. In other words, the researcher can be 95% confident (or the probability is .95) that the mean of the population represented by Group 1 is between .28 and 4.92 units larger than the mean of the population represented by Group 2. If the researcher wants to compute the 99% confidence interval for a comparison, the same procedure can be used, except for the fact that in computing the *CD* value for the comparison, the relevant .01 tabled critical *q* value is employed (or the tabled critical .01 *t*, *F*, or *t_D* value if the comparison procedure happens to employ either of the aforementioned distributions).

It should be emphasized that the range of values that define a confidence interval will be a function of the tabled critical value for the relevant test statistic that a researcher elects to employ in the analysis. As noted earlier, the tabled critical value one employs will be a function of the value established for α_{FW} . In the case of the **Bonferroni-Dunn test**, the magnitude of the critical *t_{B/D}* value one employs (and, consequently, the range of values that defines a confidence interval) increases as the number of comparisons one conducts increases.

If one has reason to believe that the homogeneity of variance assumption underlying the analysis of variance is violated, one can argue that the measure of error variability employed in computing a confidence interval should be a pooled measure of variability based only on the groups involved in a specific comparison. Under such circumstances, one can also argue that it

is acceptable to employ Equation 11.15 (employed to compute a confidence interval for the ***t* test for two independent samples**) to compute the confidence interval for a comparison. In using the latter equation for a simple comparison, one can argue that $df = n_a + n_b - 2$ (the degrees of freedom used for the ***t* test for two independent samples**) should be employed for the analysis as opposed to df_{WG} . The use of Equation 11.15 can also be justified in circumstances where: a) The researcher views the groups involved in a comparison as distinct (with respect to both the value of μ and σ^2) from the other groups involved in the study; and b) The researcher is not attempting to control the value of α_{FW} .

In view of everything that has been said, it should be apparent that the value of a confidence interval can vary dramatically depending upon which of the comparison procedures a researcher employs, and what assumptions one is willing to make with reference to the underlying populations under study. For this reason, two researchers may compute substantially different confidence intervals as a result of employing different comparison procedures. In the final analysis, however, each of the researchers may be able to offer a persuasive argument in favor of the methodology he employs.

2. Comparing the means of three or more groups when $k \geq 4$ Within the framework of a **single-factor between-subjects analysis of variance** involving $k = 4$ or more groups, a researcher may wish to evaluate a general hypothesis with respect to the means of a subset of groups, where the number of groups in the subset is some value less than k . Although the latter type of situation is not commonly encountered in research, this section will describe the protocol for conducting such an analysis.

To illustrate, assume that a fourth group is added to Example 21.1. Assume that the scores of the five subjects who serve in Group 4 are as follows: 3, 2, 1, 4, 5. Thus, $\Sigma X_4 = 15$, $\bar{X}_4 = 3$, and $\Sigma X_4^2 = 55$. If the data for Group 4 are integrated into the data for the other three groups whose performance is summarized in Table 21.1, the following summary values are computed: $N = nk = (5)(4) = 20$, $\Sigma X_T = 125$, $\Sigma X_T^2 = 911$. Substituting the revised values for $k = 4$ groups in Equations 21.2, 21.3, and 21.4/21.5, the following sum of squares values are computed: $SS_T = 129.75$, $SS_{BG} = 96.95$, $SS_{WG} = 32.8$. Employing the values $k = 4$ and $N = 20$ in Equations 21.8 and 21.9, the values $df_{BG} = 4 - 1 = 3$ and $df_{WG} = 20 - 4 = 16$ are computed. Substituting the appropriate values for the sum of squares and degrees of freedom in Equations 21.6 and 21.7, the values $MS_{BG} = 96.95/3 = 32.32$ and $MS_{WG} = 32.8/16 = 2.05$ are computed. Equation 21.12 is employed to compute the value $F = 32.32/2.05 = 15.77$. Table 21.6 is the summary table of the analysis of variance.

**Table 21.6 Summary Table of Analysis of Variance
for Example 21.1 When $k = 4$**

Source of variation	<i>SS</i>	<i>df</i>	<i>MS</i>	<i>F</i>
Between-groups	96.95	3	32.32	15.77
Within-groups	32.80	16	2.05	
Total	129.75	19		

Employing $df_{num} = 3$ and $df_{den} = 16$, the tabled critical .05 and .01 values are $F_{.05} = 3.24$ and $F_{.01} = 5.29$. Since the obtained value $F = 15.77$ is greater than both of the aforementioned critical values, the null hypothesis (which for $k = 4$ is $H_0: \mu_1 = \mu_2 = \mu_3 = \mu_4$) can be rejected at both the .05 and .01 levels.

Let us assume that prior to the above analysis the researcher has reason to believe that Groups 1, 2, and 3 may be distinct from Group 4. However, before he contrasts the composite

mean of Groups 1, 2, and 3 with the mean of Group 4 (i.e., conducts the complex comparison which evaluates the null hypothesis $H_0: (\mu_1 + \mu_2 + \mu_3)/3 = \mu_4$), he decides to evaluate the null hypothesis $H_0: \mu_1 = \mu_2 = \mu_3$. If the latter null hypothesis is retained, he will assume that the three groups share a common mean value and, on the basis of this, he will compare their composite mean with the mean of Group 4. In order to evaluate the null hypothesis $H_0: \mu_1 = \mu_2 = \mu_3$, it is necessary for the researcher to conduct a separate analysis of variance that just involves the data for the three groups identified in the null hypothesis. The latter analysis of variance has already been conducted, since it is the original analysis of variance that is employed for Example 21.1 — the results of which are summarized in Table 21.2.

Upon conducting an analysis of variance on the data for all $k = 4$ groups as well as an analysis of variance on the data for the subset comprised of $k_{\text{subset}} = 3$ groups, the researcher has the necessary information to compute the appropriate F ratio (which will be represented with the notation $F_{(1/2/3)}$) for evaluating the null hypothesis $H_0: \mu_1 = \mu_2 = \mu_3$. In computing the F ratio to evaluate the latter null hypothesis, the following values are employed: a) $MS_{BG} = 26.53$ (which is the value of MS_{BG} computed for the analysis of variance in Table 21.2 that involves only the three groups identified in null hypothesis $H_0: \mu_1 = \mu_2 = \mu_3$) is employed as the numerator of the F ratio; and b) $MS_{WG} = 2.05$ (which is the value of MS_{WG} computed in Table 21.6 for the omnibus F test when the data for all $k = 4$ groups are evaluated) is employed as the denominator of the F ratio. The reason for employing the latter value instead of $MS_{WG} = 1.9$ (which is the value of MS_{WG} computed for the analysis of variance in Table 21.2 that only employs the data for the three groups identified in the null hypothesis $H_0: \mu_1 = \mu_2 = \mu_3$) is because $MS_{WG} = 2.05$ is a pooled estimate of all $k = 4$ population variances. If, in fact, the populations represented by all four groups have equal variances, this latter value will provide the most accurate estimate of MS_{WG} . Thus:

$$F_{(1/2/3)} = \frac{MS_{BG_{(1/2/3)}}}{MS_{WG_{(1/2/3/4)}}} = \frac{13.27}{2.05} = 6.47$$

The degrees of freedom employed for the analysis are based on the mean square values employed in computing the $F_{(1/2/3)}$ ratio. Thus: $df_{\text{num}} = k_{\text{subset}} - 1 = 3 - 1 = 2$ (where $k_{\text{subset}} = 3$ groups) and $df_{\text{den}} = df_{WG_{(1/2/3/4)}} = 16$ (which is df_{WG} for the omnibus F test involving all $k = 4$ groups). For $df_{\text{num}} = 2$ and $df_{\text{den}} = 16$, $F_{.05} = 3.63$ and $F_{.01} = 6.23$. Since the obtained value $F = 6.47$ is greater than both of the aforementioned critical values, the null hypothesis can be rejected at both the .05 and .01 levels. Thus, the data do not support the researcher's hypothesis that Groups 1, 2, and 3 represent a homogenous subset. In view of this, the researcher would not conduct the contrast $(\bar{X}_1 + \bar{X}_2 + \bar{X}_3)/3$ versus \bar{X}_4 .

It should be noted that if the researcher has reason to believe that Groups 1, 2, and 3 have homogeneous variances, and the variance of Group 4 is not homogenous with the variance of the latter three groups, it would be more appropriate to employ $MS_{WG_{(1/2/3)}} = 1.9$ as the denominator of the F ratio as opposed to $MS_{WG_{(1/2/3/4)}} = 2.05$. With respect to the problem under discussion, since the two MS_{WG} values are almost equivalent, using either value produces essentially the same result (i.e., if $MS_{WG_{(1/2/3)}} = 1.9$ is employed to compute the $F_{(1/2/3)}$ ratio, $F_{(1/2/3)} = 13.27/1.9 = 6.98$, which is greater than both the tabled critical .05 and .01 F values).

3. Evaluation of the homogeneity of variance assumption of the single-factor between-subjects analysis of variance In Section I it is noted that one assumption of the **single-factor between-subjects analysis of variance** is homogeneity of variance. As noted in the discussion of the **t test for two independent samples**, when there are $k = 2$ groups the homogeneity of

variance assumption evaluates whether or not there is evidence to indicate an inequality exists between the variances of the populations represented by the two samples/groups. When there are two or more groups, the homogeneity of variance assumption evaluates whether there is evidence to indicate that an inequality exists between at least two of the population variances represented by the k samples/groups. When the latter condition exists it is referred to as **heterogeneity of variance**. In reference to Example 21.1, the null and alternative hypotheses employed in evaluating the homogeneity of variance assumption are as follows:

Null hypothesis $H_0: \sigma_1^2 = \sigma_2^2 = \sigma_3^2$

(The variance of the population Group 1 represents equals the variance of the population Group 2 represents equals the variance of the population Group 3 represents.)

Alternative hypothesis $H_1: \text{Not } H_0$

(This indicates that there is a difference between at least two of the three population variances.)

One of a number of procedures that can be employed to evaluate the homogeneity of variance hypothesis is **Hartley's F_{\max} test (Test 11a)**, which is also employed to evaluate homogeneity of variance for the **t test for two independent samples**.⁵² The reader is advised to review the discussion of the **F_{\max} test** under the **t test for two independent samples** prior to continuing this section.

Equation 21.37 (which is identical to Equation 11.6) is employed to compute the **F_{\max} test** statistic.

$$F_{\max} = \frac{\hat{s}_L^2}{\hat{s}_S^2} \quad \text{(Equation 21.37)}$$

Where: \hat{s}_L^2 = The largest of the estimated population variances of the k groups
 \hat{s}_S^2 = The smallest of the estimated population variances of the k groups

Employing Equation I.5, the estimated population variances are computed for the three groups.

$$\hat{s}_1^2 = \frac{426 - \frac{(46)^2}{5}}{5 - 1} = .7 \quad \hat{s}_2^2 = \frac{227 - \frac{(33)^2}{5}}{5 - 1} = 2.3 \quad \hat{s}_3^2 = \frac{203 - \frac{(31)^2}{5}}{5 - 1} = 2.7$$

The largest and smallest estimated population variances that are employed in Equation 21.37 are $\hat{s}_L^2 = \hat{s}_3^2 = 2.7$ and $\hat{s}_S^2 = \hat{s}_1^2 = .7$. Substituting the latter values in Equation 21.37, the value $F_{\max} = 3.86$ is computed.

$$F_{\max} = \frac{2.7}{.7} = 3.86$$

The value of F_{\max} will always be a positive number that is greater than 1 (unless $\hat{s}_L^2 = \hat{s}_S^2$, in which case $F_{\max} = 1$). The F_{\max} value obtained with Equation 21.37 is evaluated with **Table A9 (Table of the F_{\max} Distribution)** in the **Appendix**. Since in Example 21.1, there are $k = 3$ groups and $n = 5$ subjects per group, the tabled critical values in **Table A9** that are employed are the values in the cell that is the intersection of the row $n - 1 = 4$ and the column $k = 3$. In order to reject the null hypothesis, and thus conclude that the homogeneity of variance assumption is

violated, the obtained F_{\max} value must be equal to or greater than the tabled critical value at the prespecified level of significance. Inspection of [Table A9](#) indicates that for $n - 1 = 4$ and $k = 3$, $F_{\max, .05} = 15.5$ and $F_{\max, .01} = 37$. Since the obtained value $F_{\max} = 3.86$ is less than $F_{\max, .05} = 15.5$, the null hypothesis cannot be rejected. In other words, the alternative hypothesis indicating the presence of heterogeneity of variance is not supported.

Two assumptions of the F_{\max} test are: a) Each of the samples has been randomly selected from the population it represents; and b) The distribution of data in the underlying populations from which each of the samples is derived is normal. Various sources (e.g., Keppel (1991), Maxwell and Delaney (1990), and Winer *et al.* (1991)) note that when the normality assumption is violated, the accuracy of the F_{\max} test may be severely compromised. This problem becomes exacerbated when violation of the normality assumption occurs within the framework of an analysis involving small and/or unequal sample sizes. As noted in Section VI of the ***t* test for two independent samples**, the F_{\max} test assumes that there are an equal number of subjects per group. However, if the sample sizes of the groups being compared are unequal, but are approximately the same value, the value of the larger sample size can be employed to represent n in evaluating the test statistic. Kirk (1982, 1995) and Winer *et al.* (1991) note that using the larger n will result in a slight increase in the Type I error rate for the test.

One criticism of the F_{\max} test is that it is less powerful than some alternative but computationally more involved procedures for evaluating the homogeneity of variance assumption. Some of these procedures can be found in sources on analysis of variance (e.g., Keppel (1991), Kirk (1982, 1995), Maxwell and Delaney (1990), and Winer *et al.* (1991)). Among the more commonly cited alternatives to the F_{\max} test are tests developed by Bartlett (1937) and Cochran (1941). Although both of these tests do use more information than the F_{\max} test, they are also subject to distortion when the underlying populations are not normally distributed. Winer *et al.* (1991) discuss tests developed by Box (1953) and Scheffé (1959) which are not as likely to be affected by violation of the normality assumption. Keppel (1991) and Winer *et al.* (1991) note that in a review of 56 tests of homogeneity of variance, Conover *et al.* (1981) recommend a test by Brown and Forsythe (1974a, 1974b). Howell (1992, 1997) and Maxwell and Delaney (1990), on the other hand, endorse the use of a test developed by O'Brien (1981).

When all is said and done, perhaps the most reasonable approach for evaluating the homogeneity of variance hypothesis is to employ a methodology suggested by Keppel (1991) (also discussed in Keppel *et al.* (1992)). Keppel (1991) recommends the use of the F_{\max} test in evaluating the homogeneity of variance hypothesis, but notes that regardless of the values of n or k , if $F_{\max} \geq 3$ a lower level of significance (i.e., a lower α value) should be employed in evaluating the results of the analysis of variance in order to avoid inflating the Type I error rate associated with the latter test. Keppel's (1991) strategy is based on research which indicates that when $F_{\max} \geq 3$, there is an increased likelihood that the accuracy of the tabled critical values in the F distribution will be compromised. The fact that the value $F_{\max} = 3$ is considerably lower than most of the tabled critical F_{\max} values in [Table A9](#), reinforces what was noted earlier concerning the power of the F_{\max} test — specifically, the low power of the test may increase the likelihood of committing a Type II error (i.e., not rejecting the null hypothesis when heterogeneity of variance is present).

When, in fact, the homogeneity of variance assumption is violated, there is an increased likelihood of committing a Type I error in conducting the analysis of variance evaluating the k group means. Factors that influence the degree to which the Type I error rate for the analysis of variance will be larger than the prespecified value of alpha are the size of the samples and the shapes of the underlying population distributions. Sources generally agree that the effect of violation of the homogeneity of variance assumption on the accuracy of the tabled critical F values is exacerbated when there are not an equal number of subjects in each group.

A variety of strategies have been suggested regarding how a researcher should deal with heterogeneity of variance. Among the procedures that have been suggested are the following: a) Keppel (1991) notes that one option available to the researcher is to employ an adjusted tabled critical F value in evaluating the analysis of variance. Specifically, one can employ a tabled critical value associated with a lower alpha level than the prespecified alpha level, so as to provide a more accurate estimate of the latter value (i.e., employ $F_{.025}$ or $F_{.01}$ to estimate $F_{.05}$). The problem with this strategy is that if too low an alpha value is employed, the power of the omnibus F test may be compromised to an excessive degree. Loss of power, however, can be offset by employing a large sample size; b) The data can be evaluated with a procedure other than an analysis of variance. Thus, one can employ a rank-order nonparametric procedure such as the **Kruskal–Wallis one-way analysis of variance by ranks (Test 22)**. However, by virtue of rank-ordering the data, the latter test will usually provide a less powerful test of an alternative hypothesis than the analysis of variance. Another option is to employ the **van der Waerden normal scores test for k independent samples (Test 23)**, which is a nonparametric procedure that under certain conditions can be as or more powerful than the analysis of variance. A number of alternative parametric procedures developed by Brown and Forsythe (1974a, 1974c), James (1951), and Welch (1951) are discussed in various sources. Keppel (1991) notes, however, that the Brown and Forsythe and Welch procedures are not acceptable when $k > 4$, and that James' procedure is too computationally involved for conventional use. In addition, some sources believe that the aforementioned procedures have not been sufficiently researched to justify their use as an alternative to the analysis of variance, even if the homogeneity of variance assumption of the latter test is violated; and c) Another option available to the researcher is to equate the estimated population variances by employing a data transformation procedure (discussed in Section VII of the **t test for two independent samples**), and to conduct an analysis of variance on the transformed data.

4. Computation of the power of the single-factor between-subjects analysis of variance

Prior to reading this section the reader may find it useful to review the discussion on power in Section VI of both the **single-sample t test (Test 2)** and the **t test for two independent samples**. Before conducting an analysis of variance a researcher may want to determine the minimum sample size required in order to detect a specific effect size. To conduct such a power analysis, the researcher will have to estimate the means of all of the populations that are represented by the experimental treatments/groups. Additionally, he will have to estimate a standard deviation value which it will be assumed represents the standard deviation of all k populations. Understandably, the accuracy of one's power calculations will be a function of the researcher's ability to come up with good approximations for the means and standard deviations of the populations that are involved in the study. The basis for making such estimates will generally be prior research concerning the hypothesis under study.

Equation 21.38 is employed for computing the power of the **single-factor between-subjects analysis of variance**. The test statistic ϕ represents what is more formally known as the **noncentrality parameter**, and is based on the **noncentral F distribution**.⁵³

$$\phi = \sqrt{n \left[\frac{\sum (\mu_j - \mu_T)^2}{k \sigma_{WG}^2} \right]} \quad (\text{Equation 21.38})$$

Where: μ_j = The estimated mean of the population represented by Group j
 μ_T = The grand mean, which is the average of the k estimated population means

σ_{WG}^2 = The estimated population variance for each of the k groups
 n = The number of subjects per group
 k = The number of groups

The computation of the minimum acceptable sample size required to achieve a specified level of power is generally determined prior to collecting the data for an experiment. Using trial and error, a researcher can determine what value of n (based on the assumption that there are an equal number of subjects per group) when substituted in Equation 21.38 will yield the desired level of power. To illustrate the use of Equation 21.38 with Example 21.1, let us assume that prior to conducting the study the researcher estimates that the means of the populations represented by the three groups are as follows: $\mu_1 = 10$, $\mu_2 = 8$, $\mu_3 = 6$. Additionally, it will be assumed that he estimates that the variance for each of the three populations the groups represent is $\sigma_{WG}^2 = 2.5$.⁵⁴ Based on this information, the value $\mu_T = 8$ can be computed: $\mu_T = (\mu_1 + \mu_2 + \mu_3)/k = (10 + 8 + 6)/3 = 8$. The appropriate values are now substituted in Equation 21.38.

$$\phi = \sqrt{n \left[\frac{(10 - 8)^2 + (8 - 8)^2 + (6 - 8)^2}{(3)(2.5)} \right]} = \sqrt{1.07n} = 1.03\sqrt{n}$$

At this point, **Table A15 (Graphs of the Power Function for the Analysis of Variance)** in the **Appendix** can be employed to determine the necessary sample size required in order to have the power stipulated by the experimenter. **Table A15** is comprised of sets of power curves that were derived by Pearson and Hartley (1951). Each set of curves is based on a different value for df_{num} , which in the case of a **single-factor between-subjects analysis of variance** is df_{BG} employed for the omnibus F test. Within each set of curves, for a given value of df_{num} there are power functions for both $\alpha = .05$ and $\alpha = .01$. For our analysis (for which it will be assumed that $\alpha = .05$) the appropriate set of curves to employ is the set for $df_{num} = df_{BG} = 2$. Let us assume we want the omnibus F test to have a power of at least .80. We now substitute what we consider to be a reasonable value for n in the equation $\phi = 1.03\sqrt{n}$ (which is the result obtained with Equation 21.38). To illustrate, the value $n = 5$ (the sample size employed for Example 21.1) is substituted in the equation. The resulting value is $\phi = 1.03\sqrt{5} = 2.30$.

The value $\phi = 2.30$ is located on the abscissa (X -axis) of the relevant set of curves in **Table A15** — specifically, the set for $df_{num} = 2$. At the point corresponding to $\phi = 2.30$, a perpendicular line is erected from the abscissa which intersects with the power curve that corresponds to the value of $df_{den} = df_{WG}$ employed for the omnibus F test. Since $df_{WG} = 12$, the curve for the latter value is employed.⁵⁵ At the point the perpendicular intersects the curve $df_{WG} = 12$, a second perpendicular line is drawn in relation to the ordinate (Y -axis). The point at which this perpendicular intersects the ordinate indicates the power of the test. Since $\phi = 2.30$, we determine the power equals .89. Thus, if we employ five subjects per group, there is a probability of .89 of detecting an effect size equal to or larger than the one stipulated by the researcher (which is a function of the estimated values for the population means relative to the value estimated for the variance of a population). Since the probability of committing a Type II error is $\beta = 1 - \text{power}$, $\beta = 1 - .89 = .11$. The latter value represents the likelihood of not detecting an effect size equal to or greater than the one stipulated.

Cohen (1977, 1988), who provides a detailed discussion of power computations for the analysis of variance, describes a measure of effect size for the analysis of variance based on standard deviation units that is comparable to the d value computed for the different types of t tests. In the case of the analysis of variance, d is the difference between the smallest and

largest of the estimated population means divided by the standard deviation of the populations. In other words, $d = (\mu_L - \mu_S)/\sigma$. In our example the largest estimated population mean is $\mu_1 = 10$ and the smallest is $\mu_3 = 6$. The value of σ is $\sigma_{WG} = \sqrt{\sigma_{WG}^2} = \sqrt{2.5} = 1.58$. Thus, $d = (10 - 6)/1.58 = 2.53$. This result tells us that if $n = 5$, a researcher has a .89 probability of detecting a difference of about two and one-half standard deviation units.

It is also possible to conduct a power analysis for comparisons that are conducted following the computation of the omnibus F value. In fact, Keppel (1991) recommends that the sample size employed in an experiment be based on the minimum acceptable power necessary to detect the smallest effect size among all of the comparisons the researcher plans before collecting the data. The value ϕ_{comp} (described by McFatter and Gollob (1986)), which is computed with Equation 21.39, is employed to determine the power of a comparison.

$$\phi_{comp} = \sqrt{n \left[\frac{(\mu_a - \mu_b)^2}{2(\sigma_{WG}^2)(\sum c_j^2)} \right]} \quad (\text{Equation 21.39})$$

Equation 21.39 can be used for both simple and complex single degree of freedom comparisons. As a general rule, the equation is used for planned comparisons. Although it can be extended to unplanned comparisons, published power tables for the analysis of variance generally only apply to per comparison error rates of $\alpha = .05$ and $\alpha = .01$. In the case of planned and especially unplanned comparisons which involve α_{PC} rates other than .05 or .01, more detailed tables are required.⁵⁶

For single degree of freedom comparisons, the power curves in [Table A15](#) for $df_{num} = 1$ are always employed. The use of Equation 21.39 will be illustrated for the simple comparison Group 1 versus Group 2 (summarized in [Table 21.3](#)). Since $\sum c_j^2 = 2$, and we have estimated $\mu_a = \mu_1 = 10$, $\mu_b = \mu_2 = 8$, and $\sigma_{WG}^2 = 2.5$, the following result is obtained.

$$\phi_{comp} = \sqrt{n \left[\frac{(10 - 8)^2}{(2)(2.5)(2)} \right]} = \sqrt{.4n} = .63\sqrt{n}$$

Substituting $n = 5$ in the equation $\phi_{comp} = .63\sqrt{n}$, we obtain $\phi_{comp} = .63\sqrt{5} = 1.41$. Employing the power curves for $df_{num} = 1$ with $\alpha = .05$, we use the curve for $df_{WG} = 12$ (the df_{WG} employed for the omnibus F test), and determine that when $\phi_{comp} = 1.41$, the power of the test is approximately .44.

It should be noted that if the methodology described for computing the power of the ***t* test for two independent samples** is employed for the above comparison or any other simple comparison, it will produce the identical result. To demonstrate that Equation 21.39 produces a result that is equivalent to that obtained with the protocol for computing the power of the ***t* test for two independent samples**, Equations 11.10 and 11.12 will be employed to compute the power of the comparison Group 1 versus Group 2. Employing Equation 11.10:

$$d = \frac{\mu_1 - \mu_2}{\sigma} = \frac{10 - 8}{1.58} = 1.27$$

Substituting the value of d in Equation 11.12, the value $\delta = 2.01$ is computed.

$$\delta = d \sqrt{\frac{n}{2}} = 1.27 \sqrt{\frac{5}{2}} = 2.01$$

The value of $\delta = 2.01$ is evaluated with **Table A3 (Power Curves for Student's t Distribution)** in the **Appendix**. A full description of how to employ the power curves in **Table A3** can be found in Section VI of the **single-sample t test**. Employing **Table A3-C** (which is the set of curves for a two-tailed analysis with $\alpha = .05$), we use the curve for $df_{WG} = 12$. It is determined that when $\delta = 2.01$, the power of the comparison is approximately .44.

A final note regarding Equation 21.39: The value of Σc_j^2 computed for a complex comparison will always be lower than the value Σc_j^2 computed for a simple comparison (in the case of a simple comparison, Σc_j^2 will always equal 2). Because of this, for a fixed value of n the computed value of ϕ_{comp} will always be larger for a complex comparison and, consequently, the power of a complex comparison will always be greater than the power of a simple comparison.

5. Measures of magnitude of treatment effect for the single-factor between-subjects analysis of variance: Omega squared (Test 21g), eta squared (Test 21h), and Cohen's f index (Test 21i) Prior to reading this section the reader should review the discussion of the measures of magnitude of treatment effect in Section VI of the **t test for two independent samples**. As is the case with the t value computed for the latter test, the omnibus F value computed for the **single-factor between-subjects analysis of variance** only provides a researcher with information regarding whether the null hypothesis can be rejected — i.e., whether a significant difference is present between at least two of the experimental treatments. The F value (as well as the level of significance with which it is associated), however, does not provide the researcher with any information regarding the size of any treatment effect that is present. As is the case with a t value, an F value is a function of both the difference between the means of the experimental treatments and the sample size. The measures described in this section are variously referred to as **measures of effect size, measures of magnitude of treatment effect, measures of association, and correlation coefficients**.

Omega squared (Test 21g) A number of measures of the **magnitude of treatment effect** have been developed which can be employed for the **single-factor between-subjects analysis of variance**. Such measures, which are independent of sample size, provide an estimate of the proportion of variability on the dependent variable that is associated with the independent variable/experimental treatments. Although sources are not in total agreement with respect to which measure of treatment effect is most appropriate for the **single-factor between-subjects analysis of variance**, one commonly employed measure is the **omega squared** statistic (ω^2), which provides an estimate of the underlying population parameter ω^2 . The value of ω^2 is computed with Equation 21.41. The ω^2 value computed with Equation 21.41 is the best estimate of the proportion of variability in the data that is attributed to the experimental treatments. It is obtained by dividing treatment variability (σ_{BG}^2) by total variability (which equals $\sigma_{BG}^2 + \sigma_{WG}^2$). Thus, Equation 21.40 represents the population parameter estimated by Equation 21.41.

$$\omega^2 = \frac{\sigma_{BG}^2}{\sigma_{BG}^2 + \sigma_{WG}^2} \quad (\text{E equation 21.40})$$

$$\hat{\omega}^2 = \frac{SS_{BG} - (k - 1)MS_{WG}}{SS_T + MS_{WG}} \quad (\text{E equation 21.41})$$

Although the value of $\hat{\omega}^2$ will generally fall in the range between 0 and 1, when $F < 1$ $\hat{\omega}^2$ will be a negative number. The closer $\hat{\omega}^2$ is to 1, the stronger the association between the

independent and dependent variables, whereas the closer $\tilde{\omega}^2$ is to 0, the weaker the association between the two variables. A $\tilde{\omega}^2$ value equal to or less than 0 indicates that there is no association between the variables. Keppel (1991) notes that in behavioral science research (which is commonly characterized by a large amount of error variability) the value of $\tilde{\omega}^2$ will rarely be close to 1.

Employing Equation 21.41 with the data for Example 21.1, the value $\tilde{\omega}^2 = .44$ is computed.

$$\tilde{\omega}^2 = \frac{26.53 - (3 - 1)(1.9)}{49.33 + 1.9} = .44$$

Equation 21.42 is an alternative equation for computing the value of $\tilde{\omega}^2$ that yields the same value as Equation 21.41.⁵⁷

$$\tilde{\omega}^2 = \frac{(k - 1)(F - 1)}{(k - 1)(F - 1) + nk} \quad \text{(Equation 21.42)}$$

$$\tilde{\omega}^2 = \frac{(2)(6.98 - 1)}{(2)(6.98 - 1) + (5)(3)} = .44$$

The value $\tilde{\omega}^2 = .44$ indicates that 44% (or a proportion of .44) of the variability on the dependent variable (the number of nonsense syllables correctly recalled) is associated with variability on the levels of the independent variable (noise). To say it another way, 44% of the variability on the recall scores of subjects can be accounted for on the basis of which group a subject is a member. As noted in the discussion of **omega squared** in Section VI of the **t test for two independent samples**, Cohen (1977; 1988, pp. 284–287) has suggested the following (admittedly arbitrary) values, which are employed in psychology and a number of other disciplines, as guidelines for interpreting $\tilde{\omega}^2$: a) A **small effect size** is one that is greater than .0099 but not more than .0588; b) A **medium effect size** is one that is greater than .0588 but not more than .1379; c) A **large effect size** is greater than .1379. If one employs Cohen's (1977, 1988) guidelines for magnitude of treatment effect, $\tilde{\omega}^2 = .44$ represents a large treatment effect.

Eta squared (Test 16h) Another measure of treatment effect employed for the **single-factor between-subjects analysis of variance** is the **eta squared** statistic ($\tilde{\eta}^2$) (which estimates the underlying population parameter η^2). $\tilde{\eta}^2$ is computed with Equation 21.43.

$$\tilde{\eta}^2 = \frac{SS_{BG}}{SS_T} \quad \text{(Equation 21.43)}$$

Employing Equation 21.43 with the data for Example 21.1, the value $\tilde{\eta}^2 = .54$ is computed.

$$\tilde{\eta}^2 = \frac{26.53}{49.33} = .54$$

Note that the value $\tilde{\eta}^2 = .54$ is larger than $\tilde{\omega}^2 = .44$ computed with Equations 21.41/21.42. Sources note that $\tilde{\eta}^2$ is a more biased estimate of the magnitude of treatment effect in the underlying population than is $\tilde{\omega}^2$, since $\tilde{\eta}^2$ employs the values SS_{BG} and SS_T , which by themselves are biased estimates of population variability. Darlington and Carlson (1987) note that Equation 21.44 can be employed to compute a less biased estimate of the population parameter that is estimated by $\tilde{\eta}^2$.

$$\text{Adjusted } \hat{\eta}^2 = 1 - \frac{MS_{WG}}{MS_T} \quad (\text{Equation 21.44})$$

$$\text{Where: } MS_T = \frac{SS_T}{N - 1}$$

Since $MS_T = 49.33/14 = 3.52$, the adjusted $\hat{\eta}^2 = .46$ falls in between $\hat{\omega}^2 = .44$ and $\hat{\eta}^2 = .54$ computed with Equations 21.41/21.42 and Equation 21.43.

$$\text{Adjusted } \hat{\eta}^2 = 1 - \frac{1.9}{3.52} = .46$$

When $\hat{\omega}^2$ and $\hat{\eta}^2$ are based on a small sample size, their standard error (which is a measure of error variability) will be large and, consequently, the reliability of the measures of treatment effect will be relatively low. The latter will be reflected in the fact that under such conditions a confidence interval computed for a measure of treatment effect (the computation of which will not be described in this book) will have a wide range. It should be emphasized that a measure of magnitude of treatment effect is a measure of association/correlation and, in and of itself, it is not a test of significance. The significance of $\hat{\omega}^2$ and $\hat{\eta}^2$ is based on whether or not the omnibus F value is significant.⁵⁸

Cohen's f index (Test 21i) Cohen (1977, 1988) describes an index of effect size that can be employed with the **single-factor between-subjects analysis of variance** which he designates as f . **Cohen's f index** is a generalization of his **d effect size index** in the case of three or more means. The **d index (Test 2a)** was employed to compute the power of the **single-sample t test (Test 2)**, the **t test for two independent samples**, and the **t test for two dependent samples (Test 17)**. Kirk (1995, p. 181) notes that the value of f can be computed with either Equation 21.45 or Equation 21.46. When the latter equations are employed for Example 21.1, the value $f = .89$ is obtained.

$$f = \sqrt{\frac{\hat{\omega}^2}{1 - \hat{\omega}^2}} = \sqrt{\frac{.44}{1 - .44}} = .89 \quad (\text{Equation 21.45})$$

$$f = \sqrt{\frac{\frac{k - 1}{nk} [MS_{BG} - MS_{WG}]}{MS_{WG}}} = \sqrt{\frac{\left(\frac{3 - 1}{(5)(3)}\right) [13.27 - 1.90]}{1.90}} = .89 \quad (\text{Equation 21.46})$$

It should be noted that although Cohen (1977; 1988, p. 284) employs the notation for **eta squared** in Equation 21.45 in place of **omega squared**, the definition of the statistic he uses is consistent with the definition of **omega squared**. If for Example 21.1, one elects to employ the values $\hat{\eta}^2 = .54$ or *Adjusted* $\hat{\eta}^2 = .46$ in Equation 21.45, the values $f = 1.08$ and $f = .92$ are computed.

Cohen (1977; 1988, pp. 284–288) has proposed the following (admittedly arbitrary) f values as criteria for identifying the magnitude of an effect size: a) A **small effect size** is one that is greater than .1 but not more than .25; b) A **medium effect size** is one that is greater than .25 but not more than .4; and c) A **large effect size** is greater than .4. Employing Cohen's criteria, the value $f = .89$ represents a large effect size. The f effect size index is commonly employed in computing the power of the **single-factor between-subjects analysis of variance** (as well as the

power of the analysis of variance when it is employed with other designs). Cohen (1977; 1988, Chapter 8) contains power tables for the analysis of variance that employ f as a measure of effect size.

Equation 21.47 allows one to convert an f value into an $\tilde{\omega}^2$ or **eta squared** value. (As was the case with Equation 21.45, although Cohen (1977; 1988, p. 281) employs the notation for **eta squared** in Equation 21.47 in place of **omega squared**, the definition of the statistic he uses is consistent with the definition of **omega squared**.)

$$\tilde{\omega}^2 = \frac{f^2}{1 + f^2} = \frac{(.89)^2}{1 + (.89)^2} = .44 \quad (\text{Equation 21.47})$$

If the values $f = 1.08$ and $f = .92$ are substituted in Equation 21.47, the values $\tilde{\eta}^2 = .54$ and *Adjusted* $\tilde{\eta}^2 = .46$ are computed. The choice of employing **omega squared** or **eta squared** in Equation 21.45 is up to the researcher's discretion. Let us assume that for Example 21.1, $f = .89$. Cohen's (1977, 1988) interpretation of an f value of .89 is that it represents a standard deviation of the three population means that is .89 times as large as the standard deviation of the observations within the populations. He notes that f will equal 0 when the k treatment means are equal, and continue to increase as the ratio of between-groups variability to within-groups variability gets larger.

Many sources recommend that in summarizing the results of an experiment, in addition to reporting the omnibus test statistic (e.g., an F or t value), a measure of magnitude of treatment effect also be included, since the latter can be useful in further clarifying the nature of the relationship between the independent and dependent variables. It is important to note that if the value of a measure of magnitude of treatment effect is small, it does not logically follow that the relationship between the independent and the dependent variables is trivial. There are instances when a small treatment effect may be of practical and/or theoretical value (an illustration of this is provided in Section IX (the **Addendum**) of the **Pearson product-moment correlation coefficient**, under the discussion of **meta-analysis and related topics**). It should be noted that when the independent variable is a nonmanipulated variable, it is possible that any treatment effect that is detected may be due to some variable other than the independent variable. Such studies (referred to as **ex post facto** studies) do not allow a researcher to adequately control for the potential effects of extraneous variables on the dependent variable. As a result of this, even if a large treatment effect is present, a researcher is not justified in drawing conclusions with regard to cause and effect — specifically, the researcher cannot conclude that the independent variable is responsible for group differences on the dependent variable. Other sources which discuss measures of magnitude of treatment effect for the **single-factor between-subjects analysis of variance** are Howell (1992, 1997), Keppel (1991), Kirk (1982, 1995), Maxwell and Delaney (1990), and Winer *et al.* (1991).⁵⁹ Further discussion of the indices of treatment effect discussed in this section, and the relationship between effect size and statistical power can be found in Section IX (the **Addendum**) of the **Pearson product-moment correlation coefficient** under the discussion of **meta-analysis and related topics**.

6. Computation of a confidence interval for the mean of a treatment population Prior to reading this section the reader may find it useful to review the discussion of confidence intervals in Section VI of the **single-sample t test**. Equation 21.48 can be employed to compute a confidence interval for the mean of a population represented by one of the k treatments for which an omnibus F value has been computed.⁶⁰

$$CI = \bar{X}_j \pm t_{df_{wg}} \sqrt{\frac{MS_{wg}}{n}} \quad (\text{Equation 21.48})$$

Where: $t_{df_{wg}}$ represents the tabled critical two-tailed value in the t distribution, for df_{wg} , below which a proportion (percentage) equal to $[1 - (\alpha/2)]$ of the cases falls. If the proportion (percentage) of the distribution that falls within the confidence interval is subtracted from 1 (100%), it will equal the value of α .

The use of the tabled critical t value for df_{wg} in Equation 21.48 instead of a degrees of freedom value based on the number of subjects who served in each group (i.e., $df = n - 1$) is predicated on the fact that the estimated population variance is based on the pooled variance of the k groups. If, however, there is reason to believe that the homogeneity of variance assumption is violated, it is probably more prudent to employ Equation 2.7 to compute the confidence interval. The latter equation employs the estimated population standard deviation for a specific group for which a confidence interval is computed, rather than the pooled variability (which is represented by MS_{wg}). If the standard deviation of the group is employed rather than the pooled variability, $df = n - 1$ is used for the analysis. It can also be argued that it is preferable to employ Equation 2.7 in computing the confidence interval for a population mean in circumstances where a researcher has reason to believe that the group in question represents a population that is distinct from the populations represented by the other $(k - 1)$ groups. Specifically, if the mean value of a group is significantly above or below the means of the other groups, it can be argued that one can no longer assume that the group shares a common variance with the other groups. In view of this, one can take the position that the variance of the group is the best estimate of the variance of the population represented by that group (as opposed to the pooled variance of all of the groups involved in the study). The point to be made here is that, as is the case in computing a confidence interval for a comparison, depending upon how one conceptualizes the data, more than one methodology can be employed for computing a confidence interval for a population mean.

The computation of the 95% confidence interval for the mean of the population represented by Group 1 is illustrated below employing Equation 21.48. The value $t_{.05} = 2.18$ is the tabled critical two-tailed $t_{.05}$ value for $df_{wg} = 12$.

$$CI_{.95} = 9.2 \pm 2.18 \sqrt{\frac{1.9}{5}} = 9.2 \pm 1.34$$

Thus, the researcher can be 95% confident (or the probability is .95) that the mean of the population represented by Group 1 falls within the range 7.86 to 10.54. Stated symbolically: $7.86 \leq u_1 \leq 10.54$.

If, on the other hand, the researcher elects to employ Equation 2.7 to compute the confidence interval for the mean of the population represented by Group 1, the standard deviation of Group 1 is employed in lieu of the pooled variability of all the groups. In addition, the tabled critical two-tailed $t_{.05}$ value for $df = n - 1 = 4$ is employed in Equation 2.7. The computations are shown below.

$$\tilde{s}_1 = \sqrt{\frac{\sum X_1^2 - \frac{(\sum X_1)^2}{n}}{n - 1}} = \sqrt{\frac{426 - \frac{(46)^2}{5}}{4}} = .837$$

$$CI_{.95} = \bar{X}_1 \pm t_{.05} \left(\frac{\tilde{s}_1}{\sqrt{n}} \right) = 9.2 \pm 2.78 \left(\frac{.837}{\sqrt{5}} \right) = 9.2 \pm 1.04$$

Thus, employing Equation 2.7, the range for $CI_{.95}$ is $8.16 \leq \mu_1 \leq 10.24$.⁶¹ Note that although the range of values computed with Equation 21.48 and Equation 2.7 are reasonably close to one another, the range of the confidence interval computed with Equation 21.48 is wider. Depending on the values of $t_{df_{WG}}$ versus $t_{df_{(n-1)}}$ and $\sqrt{MS_{WG}/n}$ versus $s_{\tilde{X}_j}$, there will usually be a discrepancy between the confidence interval computed with the two equations. When the estimated population variances of all k groups are equal (or reasonably close to one another), Equation 2.7 will yield a wider confidence interval than Equation 21.48, since $\sqrt{MS_{WG}/n}$ will equal $s_{\tilde{X}_g}$ and $t_{df_{WG}} < t_{df_{(n-1)}}$. In the example illustrated in this section, the reason why use of Equation 2.7 yields a smaller confidence interval than Equation 21.48 (in spite of the fact that a larger t value is employed in Equation 2.7) is because $\tilde{s}^2 = .7$ (the estimated variance of the population represented by Group 1) is substantially less than $MS_{WG} = 1.9$ (the pooled estimate of within-groups variability).

VII. Additional Discussion of the Single-Factor Between-Subjects Analysis of Variance

1. Theoretical rationale underlying the single-factor between-subjects analysis of variance

In the **single-factor between-subjects analysis of variance** it is assumed that any variability between the means of the k groups can be attributed to one or both of the following two elements: a) **Experimental error**; and b) **The experimental treatments**. When MS_{BG} (the value computed for between-groups variability) is significantly greater than MS_{WG} (the value computed for within-groups variability), it is interpreted as indicating that a substantial portion of between-groups variability is due to a treatment effect. The rationale for this is as follows.

Experimental error is random variability in the data that is beyond the control of the researcher. In an independent groups design the average amount of variability within each of the k groups is employed to represent experimental error. Thus, the value computed for MS_{WG} is the normal amount of variability that is expected between the scores of different subjects who serve in the same group. Within this framework, within-groups variability is employed as a baseline to represent variability which results from factors that are beyond an experimenter's control. The experimenter assumes that since such uncontrollable factors are responsible for within-groups differences, it is logical to assume that they can produce differences of a comparable magnitude between the means of the k groups. As long as the variability between the group means (MS_{BG}) is approximately the same as within-groups variability (MS_{WG}), the experimenter can attribute any between-groups variability to experimental error. When, however, between-groups variability is substantially greater than within-groups variability, it indicates that something over and above error variability is contributing to the variability between the k group means. In such a case, it is assumed that a treatment effect is responsible for the larger value of MS_{BG} relative to the value of MS_{WG} . In essence, if within-groups variability is subtracted from between-groups variability, any remaining variability can be attributed to a treatment effect. If there is no treatment effect, the result of the subtraction will be zero. Of course, one can never completely rule out the possibility that if MS_{BG} is larger than MS_{WG} , the larger value for MS_{BG} is entirely due to error variability. However, since the latter is unlikely, when MS_{BG} is significantly larger than MS_{WG} , it is interpreted as indicating the presence of a treatment effect.

Tables 21.7 and 21.8 will be used to illustrate the relationship between between-groups

variability and within-groups variability in the analysis of variance. Assume that both tables contain data for two hypothetical studies employing an independent groups design involving $k = 3$ groups and $n = 3$ subjects per group. In the hypothetical examples below, even though it is not employed as the measure of variability in the analysis of variance, the range (the difference between the lowest and highest score) will be used as a measure of variability. The range is employed since: a) It is simpler to employ for purposes of illustration than the variance; and b) What is derived from the range from this example can be generalized to the variance/mean squares as they are employed within the framework of the analysis of variance.

Table 21.7 presents a set of data where there is no treatment effect, since between-groups variability equals within-groups variability. In Table 21.7, in order to assess within-groups variability we do the following: a) Compute the range of each group. This is done by subtracting the lowest score in each group from the highest score in that group; and b) Compute the average range of the three groups. Since the range for all three groups equals 2, the average range equals 2 (i.e., $(2 + 2 + 2)/3 = 2$). This value will be used to represent within-groups variability (which is a function of individual differences in performance among members of the same group).

Table 21.7 Data Illustrating No Treatment Effect

Group 1	Group 2	Group 3
3	4	5
4	5	6
5	6	7
$\bar{X}_1 = 4$	$\bar{X}_2 = 5$	$\bar{X}_3 = 6$

Table 21.8 Data Illustrating Treatment Effect

Group 1	Group 2	Group 3
3	10	30
4	11	31
5	12	32
$\bar{X}_1 = 4$	$\bar{X}_2 = 11$	$\bar{X}_3 = 31$

Between-groups variability is obtained by subtracting the lowest group mean ($\bar{X}_1 = 4$) from highest group mean ($\bar{X}_3 = 6$). Thus, since $\bar{X}_3 - \bar{X}_1 = 6 - 4 = 2$, between-groups variability equals 2. As noted previously, if between-groups variability is significantly larger than within-groups variability, it is interpreted as indicating the presence of a treatment effect. Since, in the example under discussion, both between-groups and within-groups variability equal 2, there is no evidence of a treatment effect. To put it another way, if within-groups variability is subtracted from between-groups variability, the difference is zero. In order for there to be a treatment effect, a positive difference should be present.

If, for purposes of illustration, we employ the range in the F ratio to represent variability, the value of the F will equal 1 since:

$$F = \frac{\text{Between-groups variability}}{\text{Within-groups variability}} = \frac{2}{2} = 1$$

As noted previously, when $F = 1$, there is no evidence of a treatment effect, and thus the null hypothesis is retained.⁶²

Table 21.8 presents a set of data where a treatment effect is present as a result of between-groups variability being greater than within-groups variability. In Table 21.8, if we once again use the range to assess variability, within-groups variability equals 2. This is the case since the range of each group equals 2, yielding an average range of 2. The between-groups variability, on the other hand, equals 27. The latter value is the obtained by subtracting the smallest of the three group means $\bar{X}_1 = 4$ from the largest of the group means $\bar{X}_3 = 31$. Thus, $\bar{X}_3 - \bar{X}_1 = 31 - 4 = 27$. Because the value 27 is substantially larger than 2 (which is a baseline measure of error variability that will be tolerated between the group means), there is strong evidence that a treatment effect is present. Specifically, since we will assume that only 2 of the 27 units that comprise between-groups variability can be attributed to experimental error, the remaining $27 - 2 = 25$ units can be assumed to represent the contribution of the treatment effect.

If once again, for purposes of illustration, the values of the range are employed to compute the F ratio, the resulting value will be $F = 27/2 = 13.5$. As noted previously, when the value of F is substantially greater than 1, it is interpreted as indicating the presence of a treatment effect, and consequently the null hypothesis is rejected.

2. Definitional equations for the single-factor between-subjects analysis of variance In the description of the computational protocol for the **single-factor between-subjects analysis of variance** in Section IV, Equations 21.2, 21.3, and 21.5 are employed to compute the values SS_T , SS_{BG} , and SS_{WG} . The latter set of computational equations was employed, since it allows for the most efficient computation of the sum of squares values. As noted in Section IV, computational equations are derived from definitional equations which reveal the underlying logic involved in the derivation of the sums of squares. This section will describe the definitional equations for the **single-factor between-subjects analysis of variance**, and apply them to Example 21.1 in order to demonstrate that they yield the same values as the computational equations.

As noted previously, the total sum of squares (SS_T) is made up of two elements, the between-groups sum of squares (SS_{BG}) and the within-groups sum of squares (SS_{WG}). The contribution of any single subject's score to the total variability in the data can be expressed in terms of a between-groups component and a within-groups component. When the between-groups component and the within-groups component are added, the sum reflects that subject's total contribution to the overall variability in the data. The contribution of all N subjects to the total variability (SS_T) and the elements that comprise it (SS_{BG} and SS_{WG}) are summarized in Table 21.9. The definitional equations described in this section employ the following notation: X_{ij} represents the score of the i^{th} subject in the j^{th} group; \bar{X}_T represents the grand mean (which is $\bar{X}_T = (\sum_{j=1}^k \sum_{i=1}^n X_{ij})/N = 110/15 = 7.33$); and \bar{X}_j represents the mean of the j^{th} group.

Equation 21.49 is the definitional equation for the **total sum of squares**.⁶³

$$SS_T = \sum_{j=1}^k \sum_{i=1}^n (X_{ij} - \bar{X}_T)^2 \quad (\text{Equation 21.49})$$

In employing Equation 21.49 to compute SS_T , the grand mean (\bar{X}_T) is subtracted from each of the N scores and each of the N difference scores is squared. The total sum of squares (SS_T) is the sum of the N squared difference scores. Equation 21.49 is computationally equivalent to Equation 21.2.

Equation 21.50 is the definitional equation for the **between-groups sum of squares**.

$$SS_{BG} = n \sum_{j=1}^k (\bar{X}_j - \bar{X}_T)^2 \quad (\text{Equation 21.50})$$

In employing Equation 21.50 to compute SS_{BG} , the following operations are carried out for

each group. The grand mean (\bar{X}_T) is subtracted from the group mean (\bar{X}_j). The difference score is squared, and the squared difference score is multiplied by the number of subjects in the group (n). After this is done for all k groups, the values that have been obtained for each group as a result of multiplying the squared difference score by the number of subjects in a group are summed. The resulting value represents the between-groups sum of squares (SS_{BG}). Equation 21.50 is computationally equivalent to Equation 21.3. An alternative but equivalent method of obtaining SS_{BG} (which is employed in deriving SS_{BG} in Table 21.9) is as follows: Within each group, for each of the n subjects the grand mean is subtracted from the group mean, each difference score is squared, and upon doing this for all k groups, the N squared difference scores are summed.

Equation 21.51 is the definitional equation for the **within-groups sum of squares**.

$$SS_{WG} = \sum_{j=1}^k \sum_{i=1}^n (X_{ij} - \bar{X}_j)^2 \quad (\text{Equation 21.51})$$

Table 21.9 Computation of Sums of Squares for Example 21.1 with Definitional Equations

	X_{ij}	$SS_{WG} = \sum_{j=1}^k \sum_{i=1}^n (X_{ij} - \bar{X}_j)^2$	$SS_{BG} = n \sum_{j=1}^k (\bar{X}_j - \bar{X}_T)^2$	$SS_T = \sum_{j=1}^k \sum_{i=1}^n (X_{ij} - \bar{X}_T)^2$
Group 1	8	$(8-9.2)^2 = 1.44$	$(9.2-7.33)^2 = 3.497$	$(8-7.33)^2 = .449$
	10	$(10-9.2)^2 = .64$	$(9.2-7.33)^2 = 3.497$	$(10-7.33)^2 = 7.129$
	9	$(9-9.2)^2 = .04$	$(9.2-7.33)^2 = 3.497$	$(9-7.33)^2 = 2.789$
	10	$(10-9.2)^2 = .64$	$(9.2-7.33)^2 = 3.497$	$(10-7.33)^2 = 7.129$
	9	$(9-9.2)^2 = .04$	$(9.2-7.33)^2 = 3.497$	$(9-7.33)^2 = 2.789$
Group 2	7	$(7-6.6)^2 = .16$	$(6.6-7.33)^2 = .533$	$(7-7.33)^2 = .109$
	8	$(8-6.6)^2 = 1.96$	$(6.6-7.33)^2 = .533$	$(8-7.33)^2 = .449$
	5	$(5-6.6)^2 = 2.56$	$(6.6-7.33)^2 = .533$	$(5-7.33)^2 = 5.429$
	8	$(8-6.6)^2 = 1.96$	$(6.6-7.33)^2 = .533$	$(8-7.33)^2 = .449$
	5	$(5-6.6)^2 = 2.56$	$(6.6-7.33)^2 = .533$	$(5-7.33)^2 = 5.429$
Group 3	4	$(4-6.2)^2 = 4.84$	$(6.2-7.33)^2 = 1.277$	$(4-7.33)^2 = 11.089$
	8	$(8-6.2)^2 = 3.24$	$(6.2-7.33)^2 = 1.277$	$(8-7.33)^2 = .449$
	7	$(7-6.2)^2 = .64$	$(6.2-7.33)^2 = 1.277$	$(7-7.33)^2 = .109$
	5	$(5-6.2)^2 = 1.44$	$(6.2-7.33)^2 = 1.277$	$(5-7.33)^2 = 5.429$
	7	$(7-6.2)^2 = .64$	$(6.2-7.33)^2 = 1.277$	$(7-7.33)^2 = .109$
		$SS_{WG} = 22.80$	$SS_{BG} = 26.535$	$SS_T = 49.335$

In employing Equation 21.51 to compute SS_{WG} , the following operations are carried out for each group. The group mean (\bar{X}_j) is subtracted from each score in the group. The difference scores are squared, after which the sum of the squared difference scores is obtained. The sum of the sum of the squared difference scores for all k groups represents the within-groups sum of squares. Equation 21.51 is computationally equivalent to Equation 21.5.

Table 21.9 illustrates the use of Equations 21.49, 21.50, and 21.51 with the data for Example 21.1.⁶⁴ The resulting values of SS_T , SS_{BG} , and SS_{WG} are identical to those obtained with the computational equations (Equations 21.2, 21.3, and 21.5). Any minimal discrepancies are the result of rounding off error.

3. Equivalency of the single-factor between-subjects analysis of variance and the t test for two independent samples when $k = 2$ Interval/ratio data for an experiment involving $k = 2$ independent groups can be evaluated with either a **single-factor between-subjects analysis of variance** or a **t test for two independent samples**. When both of the aforementioned tests are employed to evaluate the same set of data, they will yield the same result. Specifically, the following will always be true with respect to the relationship between the computed F and t values

for the same set of data: $F = t^2$ and $t = \sqrt{F}$. It will also be the case that the square of the tabled critical t value at a prespecified level of significance for $df = n_1 + n_2 - 2$ will be equal to the tabled critical F value at the same level of significance for $df_{BG} = 1$ and df_{WG} (which will be $df_{WG} = N - k = N - 2$, which is equivalent to the value $df = n_1 + n_2 - 2$ employed for the ***t* test for two independent samples**).

To illustrate the equivalency of the results obtained with the **single-factor between-subjects analysis of variance** and the ***t* test for two independent samples** when $k = 2$, an F value will be computed for Example 11.1. The value $t = -1.96$ ($t = -1.964$ if carried out to 3 decimal places) is obtained for the latter example when the ***t* test for two independent samples** is employed. When the same set of data is evaluated with the **single-factor between-subjects analysis of variance**, the value $F = 3.86$ is computed. Note that $(t = -1.964)^2 = (F = 3.86)$. Equations 21.2, 21.3, and 21.4 are employed below to compute the values SS_T , SS_{BG} , and SS_{WG} for Example 11.1. Since $k = 2$, $n = 5$, and $nk = N = 10 = 10$, $df_{BG} = 2 - 1 = 1$, $df_{WG} = N - k = 10 - 2 = 8$, and $df_T = N - 1 = 10 - 1 = 9$. The full analysis of variance is summarized in Table 21.10.

$$SS_T = 473 - \frac{(53)^2}{10} = 192.1 \quad SS_{BG} = \left[\frac{(14)^2}{5} + \frac{(39)^2}{5} \right] - \frac{(53)^2}{10} = 62.5$$

$$SS_{WG} = 192.1 - 62.5 = 129.6$$

Table 21.10 Summary Table of Analysis of Variance for Example 11.1

Source of variation	<i>SS</i>	<i>df</i>	<i>MS</i>	<i>F</i>
Between-groups	62.5	1	62.5	3.86
Within-groups	129.6	8	16.2	
Total	192.1	9		

For $df_{BG} = 1$ and $df_{WG} = 8$, the tabled critical .05 and .01 values are $F_{.05} = 5.32$ and $F_{.01} = 11.26$ (which are appropriate for a nondirectional analysis). Note that (if one takes into account rounding off error) the square roots of the aforementioned tabled critical values are (for $df = 8$) the tabled critical two-tailed values $t_{.05} = 2.31$ and $t_{.01} = 3.36$ that are employed in Example 11.1 to evaluate the value $t = -1.96$. Since the obtained value $F = 3.86$ is less than the tabled critical .05 value $F_{.05} = 5.32$, the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is not supported. The directional alternative hypothesis $H_1: \mu_1 < \mu_2$ is supported at the .05 level, since $F = 3.86$ is greater than the tabled critical one-tailed .05 value $F_{.90} = 3.46$ (the square root of which is the tabled critical one-tailed .05 value $t_{.05} = 1.86$ employed in Example 11.1). The directional alternative hypothesis $H_1: \mu_1 < \mu_2$ is not supported at the .01 level, since $F = 3.86$ is less than the tabled critical one-tailed .01 value $F_{.98} = 8.41$ (the square root of which is the tabled critical one-tailed .01 value $t_{.01} = 2.90$ employed in Example 11.1).⁶⁵ The conclusions derived from the **single-factor between-subjects analysis of variance** are identical to those reached when the data are evaluated with the ***t* test for two independent samples**.

4. Robustness of the single-factor between-subjects analysis of variance The general comments made with respect to the robustness of the ***t* test for two independent samples** (in Section VII of the latter test) are applicable to the **single-factor between-subjects analysis of variance**. Most sources state that the **single-factor between-subjects analysis of variance** is robust with respect to violation of its assumptions. Nevertheless, when either the normality and/or homogeneity of variance assumption is violated, it is recommended that a more conservative analysis be conducted (i.e., employ the tabled $F_{.01}$ value or even a tabled value for a lower alpha level to

represent the $F_{.05}$ value). When the violation of one or both assumptions is extreme, some sources recommend that a researcher consider employing an alternative procedure. Alternative procedures are discussed earlier in this section under the homogeneity of variance assumption. Keppel (1991) and Maxwell and Delaney (1990) provide comprehensive discussions on the general subject of the robustness of the **single-factor between-subjects analysis of variance**.

5. Fixed-effects versus random-effects models for the single-factor between-subjects analysis of variance The terms **fixed-** versus **random-effects models** refer to the way in which a researcher selects the levels of the independent variables that are employed in an experiment. Whereas a **fixed-effects model** assumes that the levels of the independent variable are the same levels that will be employed in any attempted replication of the experiment, a **random-effects model** assumes that the levels have been randomly selected from the overall population of all possible levels that can be employed for the independent variable. The discussion of the **single-factor between-subjects analysis of variance** in this book assumes a **fixed-effects model**. With the exception of the computation of measures of magnitude of treatment effect, the equations employed for the fixed-effects model are identical to those that are employed for a random-effects model. However, in the case of more complex designs (within-subjects and factorial designs), the computational procedures for fixed- versus random-effects models may differ.⁶⁶ The degree to which a researcher may generalize the results of an experiment will be a direct function of which model is employed. Specifically, if a fixed-effects model is employed, one can only generalize the results of an experiment to the specific levels of the independent variable that are used in the experiment. On the other hand, if a random-effects model is employed, one can generalize the results to all possible levels of the independent variable.

6. Multivariate analysis of variance (MANOVA) The **multivariate** analog of the **single-factor between-subjects analysis of variance** is the **multivariate analysis of variance (MANOVA)**, which is one of a number multivariate statistical procedures discussed in the book. As noted under the discussion of **Hotelling's T^2** (discussed in Section VII of the **t test for two independent samples**), the term multivariate is employed in reference to procedures that evaluate experimental designs in which there are multiple independent variables and/or multiple dependent variables. The **MANOVA** is a generalization of **Hotelling's T^2** to experimental designs involving more than two groups. In point of fact, **Hotelling's T^2** represents a special case of the **multivariate analysis of variance (MANOVA)**. The **MANOVA** can be employed to analyze the data for an experiment that involves a single independent variable comprised of two or more levels and multiple dependent variables. With regard to the latter, instead of a single score, each subject produces scores on two or more dependent variables. To illustrate, let us assume that in Example 21.1 two scores are obtained for each subject. One score represents the number of correct responses, and a second score represents response latency (i.e., speed of response). Within the framework of the **MANOVA**, a composite mean based on both the number of correct responses and response latency scores is computed for each group. The latter composite means are referred to as **mean vectors** or **centroids**. As is the case with the **single-factor between-subjects analysis of variance**, the means (in this case, composite) for the three groups are then compared with one another.

Stevens (1996) notes the following reasons why a researcher should consider employing a **MANOVA** instead of an analysis of variance procedure which evaluates just a single dependent variable: a) Most treatments that have an effect on subjects will impact them in a variety of ways. Consequently, an experimental design that evaluates multiple effects accruing from a treatment will provide a more comprehensive picture of the overall impact of the treatment; b) As noted in Section VI, conducting multiple statistical tests can inflate the overall Type I error rate associated

with a body of data. By employing multiple dependent variables within the framework of a single study, a researcher can avoid the inflated Type I error rate that can result from conducting separate studies, with each one requiring an analysis of a single dependent variable; c) Univariate analysis of variance does not take into consideration that two or more potential dependent variables may be correlated with one another, whereas a **MANOVA** takes such intercorrelations into account in computing the **MANOVA** test statistic; and d) The effect of one or more dependent variables by themselves may not be strong enough to yield a significant result, yet when employed together within the framework of a design that is evaluated with a **MANOVA**, their combined effect may be significant.

Like most multivariate procedures, the mathematics involved in conducting **MANOVA** is quite complex, and for this reason it becomes laborious if not impractical to implement without the aid of a computer. Since a full description of **MANOVA** is beyond the scope of this book, the interested reader should consult sources such as Stevens (1986, 1996) and Tabachnick and Fidell (1989, 1996) which describe multivariate procedures in detail.

VIII. Additional Examples Illustrating the Use of the Single-Factor Between-Subjects Analysis of Variance

Since the **single-factor between-subjects analysis of variance** can be employed to evaluate interval/ratio data for any independent groups design involving two or more groups, it can be used to evaluate any of the examples that are evaluated with the ***t* test for two independent samples** (with the exception of Example 11.3). Examples 21.2, 21.3, and 21.4 in this section are extensions of Examples 11.1, 11.4, and 11.5 to a design involving $k = 3$ groups. Since the data for all of the examples are identical to the data employed in Example 21.1, they yield the same result.

Example 21.2 *In order to assess the efficacy of a new antidepressant drug, 15 clinically depressed patients are randomly assigned to one of three groups. Five patients are assigned to Group 1, which is administered the antidepressant drug for a period of six months. Five patients are assigned to Group 2, which is administered a placebo during the same six-month period. Five patients are assigned to Group 3, which does not receive any treatment during the six-month period. Assume that prior to introducing the experimental treatments, the experimenter confirmed that the level of depression in the three groups was equal. After six months elapse, all 15 subjects are rated by a psychiatrist (who is blind with respect to a subject's experimental condition) on their level of depression. The psychiatrist's depression ratings for the five subjects in each group follow. (The higher the rating, the less depressed a subject.) **Group 1:** 8, 10, 9, 10, 9; **Group 2:** 7, 8, 5, 8, 5; **Group 3:** 4, 8, 7, 5, 7. Do the data indicate that the antidepressant drug is effective?*

Example 21.3 *A researcher wants to assess the relative effect of three different kinds of punishment on the emotionality of mice. Each of 15 mice is randomly assigned to one of three groups. During the course of the experiment each mouse is sequestered in an experimental chamber. While in the chamber, each of the five mice in Group 1 is periodically presented with a loud noise, each of the five mice in Group 2 is periodically presented with a blast of cold air, and each of the mice in Group 3 is periodically presented with an electric shock. The presentation of the punitive stimulus for each of the animals is generated by a machine that randomly presents the stimulus throughout the duration of the time it is in the chamber. The dependent variable of emotionality employed in the study is the number of times each mouse defecates while in the experimental chamber. The number of episodes of defecation for the 15*

mice follow: **Group 1:** 8, 10, 9, 10, 9; **Group 2:** 7, 8, 5, 8, 5; **Group 3:** 4, 8, 7, 5, 7. Do subjects exhibit differences in emotionality under the different experimental conditions?

Example 21.4 Each of three companies that manufacture the same size precision ball bearing claims it has better quality control than its competitor. A quality control engineer conducts a study in which he compares the precision of ball bearings manufactured by the three companies. The engineer randomly selects five ball bearings from the stock of Company A, five ball bearings from the stock of Company B, and five ball bearings from the stock of Company C. He measures how much the diameter of each of the 15 ball bearings deviates from the manufacturer's specifications. The deviation scores (in micrometers) for the 15 ball bearings manufactured by the three companies follow: **Company A:** 8, 10, 9, 10, 9; **Company B:** 7, 8, 5, 8, 5; **Company C:** 4, 8, 7, 5, 7. What can the engineer conclude about the relative quality control of the three companies?

IX. Addendum

Test 21j: The single-factor between subjects analysis of covariance Analysis of covariance (for which the acronym **ANCOVA** is commonly employed) is an analysis of variance procedure that employs a statistical adjustment (involving regression analysis, which is discussed under the **Pearson product-moment correlation coefficient**), to control for the effect of one or more extraneous variables on a dependent variable.⁶⁷ Although it is possible to employ multiple extraneous variables within the framework of an analysis of covariance, in this section the **single-factor between-subjects analysis of covariance** involving one extraneous variable will be discussed. Analysis of covariance is an analysis of variance procedure which utilizes data on an extraneous variable that has a linear correlation with the dependent variable. Such an extraneous variable is referred to as a **covariate** or **concomitant variable**. By utilizing the correlation between the covariate and the dependent variable, the researcher is able to remove variability on the dependent variable that is attributable to the covariate. The effect of the latter is a reduction in the error variability employed in computing the *F* ratio, thereby resulting in a more powerful test of the alternative hypothesis. A second potential effect of an analysis of covariance is that by utilizing the correlation between scores on a covariate and the dependent variable, the mean scores of the different groups can be adjusted for any pre-existing differences on the dependent variable which are present prior to the administration of the experimental treatments. Thus, one component of the analysis of covariance computations involves computing adjusted mean values for each of the *k* treatment means.

When analysis of covariance is employed, the most commonly used covariates are pretest scores on the dependent variable or subject variables such as intelligence, anxiety, weight, etc. Thus, in Example 21.1, if a researcher believes that the number of nonsense syllables a subject learns is a function of verbal intelligence, and if there is a linear correlation between verbal intelligence and one's ability to learn nonsense syllables, verbal intelligence can be employed as a covariate. In order to employ it as a covariate, it is necessary to have a verbal intelligence score for each subject who participates in the experiment. By employing the latter scores the researcher can use an analysis of covariance to determine whether there are performance differences on the dependent variable between the three groups that are independent of verbal intelligence. Later in this section an analysis of covariance will be employed to evaluate the data for Example 21.1 using verbal intelligence as a covariate.

The optimal design for which an analysis of covariance can be employed is an experiment involving a manipulated independent variable in which subjects are randomly assigned to groups, and in which scores on the covariate are measured prior to the introduction of the experimental

treatments. In such a design the analysis of covariance is able to remove variability on the dependent variable that is attributed to differences between the groups on the covariate. However when, prior to introducing the experimental treatments, it is known that a strong correlation exists between the covariate and the dependent variable, and that the groups are not equal with respect to the covariate, the following two options are available to a researcher: a) Subjects can be randomly reassigned to groups, after which the researcher can check that the resulting groups are equivalent with respect to the covariate; or b) The covariate can be integrated into the study as a second independent variable. As will be noted later, some sources endorse the use of either or both of the aforementioned strategies as preferable to employing an analysis of covariance.

A less ideal situation for employing an analysis of covariance is an experiment involving a manipulated independent variable in which subjects are randomly assigned to groups, but in which scores on the covariate are not measured until after the experimental manipulation. The latter situation is more problematical with respect to using the analysis of covariance, since subjects' scores on the covariate could have been influenced by the experimental treatments. This latter fact makes it more difficult to interpret the results of the analysis, since, in order to draw inferences with regard to cause and effect, the scores on the covariate should be independent of the treatments.

An even more problematical use of the analysis of covariance is for a design in which subjects are not randomly assigned to groups (which is often referred to as a **quasi-experimental design**). The latter can involve the use of intact groups (such as two different classes at a school) who are exposed to a manipulated independent variable, or two groups that are formed on the basis of some pre-existing subject characteristic (i.e., an **ex post facto study** involving a non-manipulated independent variable such as gender, race, etc.). It should be noted that if a substantial portion of between-groups variability can be explained on the basis of an extraneous variable (i.e., a potential covariate), it implies that there was probably some sort of systematic bias involved in forming the experimental groups. Because of the latter, it is reasonable to expect that if a researcher identifies one extraneous variable that has a substantial correlation with the dependent variable, there are probably other extraneous variables whose effects will not be controlled for, even if one evaluates the data with an analysis of covariance. In view of this, some sources (Keppel and Zedeck (1989) and Lord (1967, 1969)) argue that if subjects are not randomly assigned to groups, a researcher will not be able to adequately control for the potential effects of other pre-existing extraneous variables on the dependent variable. More specifically, they argue that the analysis of covariance will not be able to produce the necessary statistical control to allow one to unambiguously interpret the effect of the independent variable on the dependent variable. Thus, in designs in which subjects are not randomly assigned to groups, sources either state that the analysis of covariance should never be employed, or that if it is employed, the results should be interpreted with extreme caution.

Many sources (e.g., Hinkle *et al.* (1998) and Keppel (1991)) note that in order for the analysis of covariance to provide effective statistical control the following two requirements must be met: a) A linear relationship must exist between the dependent variable and the covariate (since if they are not linearly related, the adjusted mean values computed for the k experimental conditions will be biased); and b) The covariate should be independent of (i.e., not be influenced by) the experimental treatments. The simplest way to evaluate this latter requirement is to conduct an analysis of variance using the covariate as the dependent variable. If the null hypothesis of equality between the covariate treatment means is rejected, it will indicate a lack of independence between the covariate and the independent variable. Maxwell and Delaney (1990; pp. 380–385) provide an excellent description of the conditions that can result in a lack of independence between the covariate and independent variable, and the impact it will have on interpreting the results of an analysis of covariance. When a lack of independence is present, the results will be most

difficult to interpret when assignment of subjects to groups is nonrandom, and/or when the treatments effect the covariate in a situation where the covariate is measured after the administration of the treatments. Even in the ideal situation where the researcher randomly assigns subjects to the k experimental conditions and measures the covariate before introducing the experimental treatment, a researcher may detect a significant difference among the groups with respect to their means on the covariate. The latter situation could merely be representative of a Type I error — in other words, the mean differences on the covariate represent a fluke of chance variation. Under such circumstances, to insure minimal ambiguity in interpreting the results of an analysis of covariance, the most prudent strategy would probably be to randomly reassign subjects until the k covariate treatment means are approximately the same. Maxwell and Delaney (1990) note that within the framework of an analysis of covariance, the accuracy of the adjusted means which are computed for the dependent variable decreases as the group means on the covariate deviate from the grand mean on the covariate. What the latter translates into is (assuming the covariate is, in fact, independent of the independent variable) that when the treatments differ with respect to covariate means, the adjusted values of the dependent variable will be less likely to result in a significant difference — in other words, the power of the analysis of covariance to detect a significant effect between the treatment means on the dependent variable will be reduced. It is worth noting that some sources (e.g., Maxwell and Delaney (1990)) take the position that although problems in interpretation will result if the covariate is not independent of the experimental treatments, it does not necessarily mean that under such conditions an analysis of covariance cannot yield useful information.

Kachigan (1986), among others, notes that one should never use an analysis of covariance to adjust for between-groups differences with respect to a covariate that are attributable to normal sampling error. Aside from the fact that such variability is a part of expected error variability within the framework of conducting an analysis of variance, a major reason for not employing an analysis of covariance (for which the test statistic is also an omnibus F value) is that the number of within-groups degrees of freedom required for the analysis will be one less than df_{WG} required for an analysis of variance on the same set of data. In such a case, any reduction in error variance associated with the analysis of covariance may be offset by the fact that it will require a larger critical F value to reject the null hypothesis than will an analysis of variance on the original data.

Example 21.5 will be employed to illustrate the use of the **single-factor between-subjects analysis of covariance**. Example 21.5 is identical to Example 21.1, except for the fact that the covariate of verbal intelligence is included in the analysis. It is because of the latter that the data are evaluated with the **single-factor between-subjects analysis of covariance**.

Example 21.5 *A psychologist conducts a study to determine whether or not noise can inhibit learning. Each of 15 subjects is randomly assigned to one of three groups. Each subject is given 20 minutes to memorize a list of 10 nonsense syllables, which she is told she will be tested on the following day. The five subjects assigned to **Group 1**, the **no noise** condition, study the list of nonsense syllables while they are in a quiet room. The five subjects assigned to **Group 2**, the **moderate noise** condition, study the list of nonsense syllables while listening to classical music. The five subjects assigned to **Group 3**, the **extreme noise** condition, study the list of nonsense syllables while listening to rock music. The number of nonsense syllables correctly recalled by the 15 subjects follow: **Group 1**: 8, 10, 9, 10, 9; **Group 2**: 7, 8, 5, 8, 5; **Group 3**: 4, 8, 7, 5, 7. From previous research it is known that a subject's ability to learn verbal material is highly correlated with one's verbal intelligence. As a result of the latter, a test of verbal intelligence (for which the maximum possible score is 20) is administered to each subject prior to introducing the experimental treatments. The verbal intelligence scores of the subjects follow: **Group 1**: 14,*

16, 15, 16, 15; **Group 2:** 15, 17, 15, 17, 15; **Group 3:** 14, 17, 16, 16, 16. *Do the data indicate that noise influenced subjects' performance?*

The **null** and **alternative hypotheses** employed for the **single-factor between-subjects analysis of covariance** are identical to those employed for the **single-factor between-subjects analysis of variance**. The treatment means, however, that are contrasted in the analysis of covariance are adjusted values. As noted earlier, the means are adjusted for the effect of the covariate. In view of the fact that the analysis of covariance evaluates adjusted mean values, the notation μ_j' will be employed to represent the adjusted value of mean of the population the j^{th} group represents. The null and alternative hypotheses for the analysis of covariance in reference to Example 21.5 are as follows.

Null hypothesis

$$H_0: \mu_1' = \mu_2' = \mu_3'$$

(The adjusted mean of the population Group 1 represents equals the adjusted mean of the population Group 2 represents equals the adjusted mean of the population Group 3 represents.)

Alternative hypothesis

$$H_1: \text{Not } H_0$$

(This indicates there is a difference between at least two of the $k = 3$ adjusted population means.)

Computational procedures for the single-factor between-subjects analysis of covariance

This section will describe a number of computational procedures that are used within the framework of an analysis of covariance. The reader should keep in mind that the analysis of covariance can be employed with experimental designs other than a between-subjects design, and that in conducting an analysis of covariance there can be more than one covariate. All of the procedures to be described in this section, however, are in reference to the **single-factor between-subjects analysis of covariance** involving a single covariate.

The data analysis in this section will evaluate Example 21.5. In the latter example the number of nonsense syllables correctly recalled represents the dependent variable (which will be the Y variable), while the verbal intelligence test scores of subjects represent the covariate (which will be the X variable). Initially, an analysis of variance will be conducted on the covariate. The latter is generally done in order to demonstrate independence between the covariate and the experimental treatments. In the case of Example 21.5, one could argue that it is not necessary to conduct an analysis of variance on the covariate, since subjects are randomly assigned to groups, and the covariate is measured prior to the introduction of the experimental treatments. However, random assignment in and of itself does not insure that the group means on the covariate will be equal. As noted earlier, Maxwell and Delaney (1990) state that the accuracy of the adjusted means which are computed for the dependent variable will decrease as the group means on the covariate deviate from the grand mean on the covariate. Most sources agree that if the assignment of subjects to groups is nonrandom, and/or the covariate is measured before or during the administration of treatments, an analysis of variance on the covariate should be conducted. Although a nonsignificant result for the latter analysis does not guarantee that the analysis of covariance (as well as the computed values for the adjusted treatments means) will be unbiased, it makes it unlikely.

After establishing that there are no significant differences between the covariate means, an analysis of covariance will be conducted. After doing the latter, adjusted treatment means on the dependent variable will be computed for the three groups. The remainder of the section will describe or discuss the following: a) Conducting multiple comparisons on the adjusted treatment

Table 21.11 Data for Example 21.5

Group 1				
X_1	X_1^2	Y_1	Y_1^2	$X_1 Y_1$
14	196	8	64	112
16	256	10	100	160
15	225	9	81	135
16	256	10	100	160
15	225	9	81	135
$\Sigma X_1 = 76$	$\Sigma X_1^2 = 1158$	$\Sigma Y_1 = 46$	$\Sigma Y_1^2 = 426$	$\Sigma X_1 Y_1 = 702$
$\bar{X}_1 = 15.2$		$\bar{Y}_1 = 9.2$		
$SS_{X_1} = \Sigma X_1^2 - \frac{(\Sigma X_1)^2}{n_1} = 1158 - \frac{(76)^2}{5} = 2.8$				
$SS_{Y_1} = \Sigma Y_1^2 - \frac{(\Sigma Y_1)^2}{n_1} = 426 - \frac{(46)^2}{5} = 2.8$				
$SP_{1(XY)} = SP_{X_1 Y_1} = \Sigma X_1 Y_1 - \frac{(\Sigma X_1)(\Sigma Y_1)}{n_1} = 702 - \frac{(76)(46)}{5} = 2.8$				
Group 2				
X_2	X_2^2	Y_2	Y_2^2	$X_2 Y_2$
15	225	7	49	105
17	289	8	64	136
15	225	5	25	75
17	289	8	64	136
15	225	5	25	75
$\Sigma X_2 = 79$	$\Sigma X_2^2 = 1253$	$\Sigma Y_2 = 33$	$\Sigma Y_2^2 = 227$	$\Sigma X_2 Y_2 = 527$
$\bar{X}_2 = 15.8$		$\bar{Y}_2 = 6.6$		
$SS_{X_2} = \Sigma X_2^2 - \frac{(\Sigma X_2)^2}{n_2} = 1253 - \frac{(79)^2}{5} = 4.8$				
$SS_{Y_2} = \Sigma Y_2^2 - \frac{(\Sigma Y_2)^2}{n_2} = 227 - \frac{(33)^2}{5} = 9.2$				
$SP_{2(XY)} = SP_{X_2 Y_2} = \Sigma X_2 Y_2 - \frac{(\Sigma X_2)(\Sigma Y_2)}{n_2} = 527 - \frac{(79)(33)}{5} = 5.6$				
Group 3				
X_3	X_3^2	Y_3	Y_3^2	$X_3 Y_3$
14	196	4	16	56
17	289	8	64	136
16	256	7	49	112
16	256	5	25	80
16	256	7	49	112
$\Sigma X_3 = 79$	$\Sigma X_3^2 = 1253$	$\Sigma Y_3 = 31$	$\Sigma Y_3^2 = 203$	$\Sigma X_3 Y_3 = 496$
$\bar{X}_3 = 15.8$		$\bar{Y}_3 = 6.2$		
$SS_{X_3} = \Sigma X_3^2 - \frac{(\Sigma X_3)^2}{n_3} = 1253 - \frac{(79)^2}{5} = 4.8$				
$SS_{Y_3} = \Sigma Y_3^2 - \frac{(\Sigma Y_3)^2}{n_3} = 203 - \frac{(31)^2}{5} = 10.8$				
$SP_{3(XY)} = SP_{X_3 Y_3} = \Sigma X_3 Y_3 - \frac{(\Sigma X_3)(\Sigma Y_3)}{n_3} = 496 - \frac{(79)(31)}{5} = 6.2$				
$\Sigma X_T = 234$	$\Sigma X_T^2 = 3664$	$\Sigma Y_T = 110$	$\Sigma Y_T^2 = 856$	$\Sigma (XY)_T = 1725$
$SS_{T(X)} = \Sigma X_T^2 - \frac{(\Sigma X_T)^2}{N} = 3664 - \frac{(234)^2}{5} = 13.6$				
$SS_{T(Y)} = \Sigma Y_T^2 - \frac{(\Sigma Y_T)^2}{N} = 856 - \frac{(110)^2}{5} = 49.33$				
$SP_{T(XY)} = \Sigma (XY)_T - \frac{(\Sigma X_T)(\Sigma Y_T)}{N} = 1725 - \frac{(234)(110)}{15} = 9$				

means; b) Evaluating the homogeneity of regression assumption underlying the analysis of covariance; c) Computing measures of magnitude of treatment effect for the analysis of covariance; and d) Computing power for the analysis of covariance.

Table 21.11 summarizes the data for Example 21.5. As noted above, X represents the scores on the covariate, and Y represents the scores on the dependent variable. In the last column of **Table 21.11** an XY score is computed for each subject. A subject's XY score is obtained by multiplying the subject's X score by the subject's Y score. The latter values are employed in computing the sum of products, which is represented with notation SP . (The sum of products is discussed in greater detail in Section VII of the **Pearson product-moment correlation coefficient** under the discussion of **covariance**.) The general equation for the sum of products is $SP_{XY} = \sum XY - [(\sum X)(\sum Y)]/n$. All terms in **Table 21.11** with the subscript j (e.g., $\sum X_j$, $\sum Y_j$, etc., where j equals a specific group number) are based on the scores of the $n_j = 5$ subjects in the j^{th} group, while all terms with the subscript T (e.g., $\sum X_T$, $\sum Y_T$, etc.) are based on the scores of all $N = 15$ subjects.

Analysis of variance on the covariate The procedure for the analysis of variance on the covariate is identical to the procedure employed for the analysis of variance for Example 21.1, except for the fact that the covariate scores (X) are evaluated instead of the scores on the dependent variable (Y). The null and alternative hypotheses employed are identical to those employed for Example 21.1, except for the fact that they are stated in reference to the population means for the covariate. Thus, $H_0: \mu_{X_1} = \mu_{X_2} = \mu_{X_3}$ and $H_1: \text{Not } H_0$. Computation of the sums of squares for the analysis of variance on the covariate are summarized below.

$$SS_T = \sum X_T^2 - \frac{(\sum X_T)^2}{N} = 3664 - \frac{(234)^2}{15} = 13.6$$

$$SS_{BG} = \sum_{j=1}^k \left[\frac{(\sum X_j)^2}{n_j} \right] - \frac{(\sum X_T)^2}{N} = \left[\frac{(76)^2}{5} + \frac{(79)^2}{5} + \frac{(79)^2}{5} \right] - \frac{(234)^2}{15} = 1.2$$

$$SS_{WG} = SS_T - SS_{BG} = 13.6 - 1.2 = 12.4$$

Table 21.12 summarizes the analysis of variance on the covariate. The number of degrees of freedom employed are the same as those employed for Example 21.1, since the identical number of groups and subjects are employed in the analysis. Thus, $df_{BG} = 2$ and $df_{WG} = 12$. The tabled critical values employed in **Table A10** are $F_{.95} = 3.89$ and $F_{.99} = 6.93$. Since the computed value $F = .58$ is less than $F_{.05} = 3.89$, the null hypothesis cannot be rejected at the .05 level. Thus, we can conclude there is no difference between the groups with respect to their mean scores on the covariate (which are $\bar{X}_1 = 15.2$, $\bar{X}_2 = 15.8$, $\bar{X}_3 = 15.8$). As noted earlier, this is generally interpreted as indicating that the covariate is independent of the experimental treatments.

Table 21.12 Summary Table of Analysis of Variance on Covariate for Example 21.5

Source of variation	SS	df	MS	F
Between-groups	1.20	2	.60	.58
Within-groups	12.40	12	1.03	
Total	13.60	14		

The analysis of covariance In conducting the analysis of covariance we will employ the sum of squares values that were previously computed in the analysis of variance on the dependent variable and in the analysis of variance on the covariate. The values that will be employed are listed below. Note that the notation for each of the sum of squares values listed indicates whether a sum of squares value is for the X variable (the covariate) or the Y variable (the dependent variable): a) $SS_{BG(X)} = 1.2$, which represents the between-groups sum of squares for the covariate; b) $SS_{WG(X)} = 12.4$, which represents the within-groups sum of squares for the covariate; c) $SS_{T(X)} = 13.6$, which represents the total sum of squares for the covariate; d) $SS_{BG(Y)} = 26.53$, which represents the between-groups sum of squares for the dependent variable; e) $SS_{WG(Y)} = 22.8$, which represents the within-groups sum of squares for the dependent variable; and f) $SS_{T(Y)} = 49.33$, which represents the total sum of squares for the dependent variable. In addition to employing the aforementioned values, we must compute the values noted below.

a) A **between-groups sum of products**, represented by the notation $SP_{BG(XY)}$, is computed with Equation 21.52. The notation $\sum_{j=1}^k [(\sum X_j)(\sum Y_j)/n_j]$ on the right side of Equation 21.52 indicates that for each group the sum of the scores on the X variable is multiplied by the sum of the scores on the Y variable, and the product is divided by the number of subjects in the group. Upon doing the latter for all k groups, the k values that have been obtained are summed. The value $[(\sum X_T)(\sum Y_T)]/N$ is subtracted from the resulting sum. The value $[(\sum X_T)(\sum Y_T)]/N$ is obtained by multiplying the total sum of the scores on the X variable ($\sum X_T$) by the total sum of the scores on the Y variable ($\sum Y_T$), and dividing the product by the total number of subjects (N). Note that unlike a sum of squares value, a sum of products value can be a negative number.

(Equation 21.52)

$$SP_{BG(XY)} = \sum_{j=1}^k \left[\frac{(\sum X_j)(\sum Y_j)}{n_j} \right] - \frac{(\sum X_T)(\sum Y_T)}{N}$$

$$SP_{BG(XY)} = \left[\frac{(76)(46)}{5} + \frac{(79)(33)}{5} + \frac{(79)(31)}{5} \right] - \frac{(234)(110)}{15} = 1710.4 - 1716 = -5.6$$

a) A **within-groups sum of products**, represented by the notation $SP_{WG(XY)}$, is computed with Equation 21.53. As noted earlier, the notation $\sum_{j=1}^k [(\sum X_j)(\sum Y_j)/n_j]$ on the right side of Equation 21.53 indicates that for each group the sum of the scores on the X variable is multiplied by the sum of the scores on the Y variable, and the product is divided by the number of subjects in the group. Upon doing the latter for all k groups, the k values that have been obtained are summed. The resulting value is subtracted from the term $\sum(XY)_T$, which is the sum of the XY scores of all $N = 15$ subjects.

(Equation 21.53)

$$SP_{WG(XY)} = \sum(XY)_T - \sum_{j=1}^k \left[\frac{(\sum X_j)(\sum Y_j)}{n_j} \right]$$

$$SP_{WG(XY)} = 1725 - \left[\frac{(76)(46)}{5} + \frac{(79)(33)}{5} + \frac{(79)(31)}{5} \right] = 1725 - 1710.4 = 14.6$$

c) A **total sum of products**, represented by the notation $SP_{T(XY)}$, is computed with Equation 21.54. In computing the total sum of products, the value $[(\sum X_T)(\sum Y_T)]/N$ (which, as noted earlier, is obtained by multiplying the total sum of the scores on the X variable ($\sum X_T$) by the total sum of the scores on the Y variable ($\sum Y_T$), and dividing the product by the total number of subjects (N)) is subtracted from the term $\sum(XY)_T$, which, as noted earlier, is the sum of the XY scores of all $N = 15$ subjects.

(Equation 21.54)

$$SP_{T(XY)} = \Sigma(XY)_T - \frac{(\Sigma X_T)(\Sigma Y_T)}{N}$$

$$SP_{T(XY)} = 1725 - \frac{(234)(110)}{15} = 1725 - 1716 = 9$$

As is the case with the analysis of variance, sum of squares values are computed for the analysis of covariance. However, the sums of squares computed for the analysis of covariance are adjusted for the effects of the covariate. The analysis of covariance requires that the following three adjusted sum of squares values be computed: a) The **adjusted total sum of squares**, which will be represented by the notation $SS_{T(\text{adj})}$; b) The **adjusted within-groups sum of squares**, which will be represented by the notation $SS_{WG(\text{adj})}$; and c) The **adjusted between-groups sum of squares**, which will be represented by the notation $SS_{BG(\text{adj})}$.

The **adjusted total sum of squares** is computed with Equation 21.55.

(Equation 21.55)

$$SS_{T(\text{adj})} = SS_{T(Y)} - \frac{(SP_{T(XY)})^2}{SS_{T(X)}}$$

$$SS_{T(\text{adj})} = 49.33 - \frac{(9)^2}{13.6} = 43.37$$

The **adjusted within-groups sum of squares** is computed with Equation 21.56.⁶⁸

(Equation 21.56)

$$SS_{WG(\text{adj})} = SS_{WG(Y)} - \frac{(SP_{WG(XY)})^2}{SS_{WG(X)}}$$

$$SS_{WG(\text{adj})} = 22.8 - \frac{(14.6)^2}{12.4} = 5.61$$

The **adjusted between-groups sum of squares** is computed with Equation 21.57.

(Equation 21.57)

$$SS_{BG(\text{adj})} = SS_{T(\text{adj})} - SS_{WG(\text{adj})}$$

$$SS_{BG(\text{adj})} = 43.37 - 5.61 = 37.76$$

Table 21.13 summarizes the analysis of covariance.

**Table 21.13 Summary Table of Analysis of Covariance
for Example 21.5**

Source of variation	SS_{adj}	df_{adj}	MS_{adj}	F
Between-groups	37.76	2	18.88	37.02
Within-groups	5.61	11	.51	
Total	43.37	13		

Note that variability for the analysis of covariance is partitioned into between-groups variability and within-groups variability, the same two components that variability is partitioned into in the analysis of variance. As is the case for an analysis of variance, a mean square is computed for each source of variability by dividing the sum of squares by its respective degrees of freedom. Equations 21.58–21.60 summarize the computation of the degrees of freedom values. Note that in the analysis of covariance, the within-groups (error) degrees of freedom are $df_{WG(adj)} = N - k - 1$ as opposed to the value $df_{WG} = N - k$ computed for the analysis of variance. The loss of one degree of freedom in the analysis of covariance reflects the use of the covariate as a statistical control. Equations 21.61 and 21.62 summarize the computation of the mean square values, and Equation 21.63 computes the F ratio for the analysis of covariance.

$$df_{BG(adj)} = k - 1 = 3 - 1 = 2 \quad \text{(Equation 21.58)}$$

$$df_{WG(adj)} = N - k - 1 = 15 - 3 - 1 = 11 \quad \text{(Equation 21.59)}$$

$$df_{T(adj)} = N - 2 \quad \text{(Equation 21.60)}$$

$$MS_{BG(adj)} = \frac{SS_{BG(adj)}}{df_{BG(adj)}} = \frac{37.76}{2} = 18.88 \quad \text{(Equation 21.61)}$$

$$MS_{WG(adj)} = \frac{SS_{WG(adj)}}{df_{WG(adj)}} = \frac{5.61}{11} = .51 \quad \text{(Equation 21.62)}$$

$$F = \frac{MS_{BG(adj)}}{MS_{WG(adj)}} = \frac{18.88}{.51} = 37.02 \quad \text{(Equation 21.63)}$$

The obtained value $F = 37.02$ is evaluated with [Table A10](#), employing as the numerator and denominator degrees of freedom $df_{num} = df_{BG(adj)} = 2$ and $df_{den} = df_{WG(adj)} = 11$. For $df_{num} = 2$ and $df_{den} = 11$, the tabled $F_{.95}$ and $F_{.99}$ values are $F_{.05} = 3.98$ and $F_{.01} = 7.21$. In order to reject the null hypothesis, the obtained F value must be equal to or greater than the tabled critical value at the prespecified level of significance. Since $F = 37.02$ is greater than $F_{.05} = 3.98$ and $F_{.01} = 7.21$, the alternative hypothesis is supported at both the .05 and .01 levels.

Note that the value $F = 37.02$ computed for the analysis of covariance is substantially larger than the value $F = 6.98$ computed for the analysis of variance in Example 21.1. The larger F value for the analysis of covariance can be attributed to the following two factors: a) The reduction in error variability in the analysis of covariance. The latter is reflected by the fact that the **within-groups mean square** value for the analysis of covariance $MS_{WG(adj)} = .51$ is substantially less than the analogous value $MS_{WG} = 1.90$ computed for the analysis of variance; and b) The larger **between-groups mean square** computed for the analysis of covariance. With respect to the latter, in the case of the analysis of covariance $MS_{BG(adj)} = 18.88$, whereas for the analysis of variance $MS_{BG} = 13.27$.

Thus, when we contrast the result of the analysis of covariance for Example 21.5 with the result of the analysis of variance for Example 21.1, we can state that by virtue of controlling for variation attributable to the covariate we are able to conduct a more sensitive analysis with respect to the impact of the treatments on the dependent variable. As is the case for the analysis of variance, it can be concluded that there is a significant difference between at least two of the three groups exposed to different levels of noise. This result can be summarized as follows: $F(2,11) = 37.02, p < .01$.

Some sources employ the format in [Table 21.14](#) to summarize the results of an analysis of covariance.

Table 21.14 Alternative Summary Table of Analysis of Covariance for Example 21.5

Source of variation	SS_{adj}	df_{adj}	MS_{adj}	F
Covariate	5.96	1	5.96	11.65
Between-groups	37.76	2	18.88	37.02
Within-groups	5.61	11	.51	
Total	49.33	14		

Note that there are two differences between [Tables 21.13](#) and [21.14](#): a) [Table 21.14](#) contains a row for variability attributed to the covariate; and b) The total sum of squares and total degrees of freedom in the last row of [Table 21.14](#) are different than the values listed in [Table 21.13](#). In point of fact, the value for total variability in [Table 21.14](#) ($SS_T = 49.33$) is equal to the total variability computed for [Table 21.2](#) (the table for the original analysis of variance, which did not include the covariate in the study). In the same respect, the value for total degrees of freedom in [Table 21.14](#) ($df_T = 14$) is equal to the total degrees of freedom computed for [Table 21.2](#). In [Table 21.14](#) one degree of freedom is employed for the covariate, and consequently the total degrees of freedom is equal to $df = N - 1$ (which is the same value employed for the total degrees of freedom for the analysis of variance in [Table 21.2](#)). The value $SS_{\text{cov}} = 5.96$ is computed with Equation 21.64, and Equations 21.65 and 21.66 are employed to compute the values $MS_{\text{cov}} = 5.96$ and $F = 11.65$ for the covariate.

$$SS_{\text{cov}} = SS_{T(Y)} - SS_{T(\text{adj})} = 49.33 - 43.37 = 5.96 \quad (\text{Equation 21.64})$$

$$MS_{\text{cov}} = \frac{SS_{\text{cov}}}{df_{\text{cov}}} = \frac{5.96}{1} = 5.96 \quad (\text{Equation 21.65})$$

$$F = \frac{MS_{\text{cov}}}{MS_{WG(\text{adj})}} = \frac{5.96}{.51} = 11.65 \quad (\text{Equation 21.66})$$

Note that the F ratio computed for the covariate with Equation 21.66 is not the same F ratio computed for the covariate in [Table 21.12](#). Whereas the latter F ratio does not take the dependent variable into account, the value $F = 11.65$ computed with Equation 21.66 assumes the presence of both a dependent variable and a covariate in the data. Hinkle *et al.* (1998) note that the value $F = 11.65$ computed for the covariate can be employed to evaluate the null hypothesis $H_0: \rho_T = 0$, which states that in the underlying population the sample represents, the correlation between the scores of subjects on the covariate and the dependent variable equals 0 (the notation ρ is the lower case Greek letter **rho**, which is employed to represent the population correlation). Or to put it another way, the null hypothesis is stating that there is no linear relationship between the covariate and the dependent variable. The alternative hypothesis (which is nondirectional) that is evaluated is $H_1: \rho_T \neq 0$. The latter alternative hypothesis states that in the underlying population the sample represents, the correlation between the scores of subjects on the covariate and the dependent variable does not equal 0. Or to put it another way, that there is a linear relationship between the covariate and the dependent variable.

Since an assumption of the analysis of covariance is that the dependent variable and covariate are linearly related, we want to reject the null hypothesis. If the computed F ratio

computed with Equation 21.66 is statistically significant, the null hypothesis $H_0: \rho_T = 0$ can be rejected.⁶⁹ The numerator and denominator degrees of freedom employed in the analysis of the covariate F ratio are $df_{\text{num}} = df_{\text{cov}} = 1$ and $df_{\text{den}} = df_{\text{WG(adj)}} = 11$. In Table A10, for $df_{\text{num}} = 1$ and $df_{\text{den}} = 11$, the tabled $F_{.95}$ and $F_{.99}$ values are $F_{.05} = 4.84$ and $F_{.01} = 9.65$. Since $F = 11.65$ is greater than $F_{.05} = 4.84$ and $F_{.01} = 9.65$, the alternative hypothesis is supported at both the .05 and .01 levels. In other words, we can conclude there is a significant linear relationship between the dependent variable and the covariate.

It is possible to compute the following three correlation coefficients from the data in Table 21.11: a) The **overall correlation coefficient** based on the total number of scores in the three groups. The latter value, represented by the notation r_T , is computed in Endnote 69 to be $r_T = .347$; b) The **within-groups correlation coefficient** (represented by the notation r_{WG}), which is a weighted average correlation coefficient between the covariate and the dependent variable within each of the $k = 3$ groups. The within-groups correlation coefficient is computed with Equation 21.67 to be $r_{\text{WG}} = .868$. The greater the absolute value of r_{WG} , the greater the precision of the analysis of covariance;⁷⁰ and c) the **between-groups correlation coefficient** (represented by the notation r_{BG}), which is a correlation coefficient between the $k = 3$ treatment means on the covariate and the $k = 3$ treatment means on the dependent variable. The between-groups correlation coefficient is computed (employing Equation 28.1) to be $r_{\text{BG}} = -.992$. In computing the latter value, the three pairs of X and Y scores that are substituted in Equation 28.1, with $n = 3$, are $(\bar{X}_1 = 15.2, \bar{Y}_1 = 9.2)$, $(\bar{X}_2 = 15.8, \bar{Y}_2 = 6.6)$, and $(\bar{X}_3 = 15.8, \bar{Y}_3 = 6.2)$.

(Equation 21.67)

$$r_{\text{WG}} = \frac{SP_{\text{WG}(XY)}}{\sqrt{SS_{\text{WG}(X)}(SS_{\text{WG}(Y)})}} = \frac{14.6}{\sqrt{(12.4)(22.8)}} = .868$$

Kirk (1995, p. 719) notes that if the value of r_{BG} is larger than the value of r_{WG} , any reduction in error variability has a high likelihood of being offset by a reduction in between-groups variability. As a result of the latter, the F value computed for the analysis of covariance may actually be lower than the F value computed for the analysis of variance on the dependent variable. However, if r_{BG} is negative and r_{WG} is positive (as is the case in our example), the F value computed for the analysis of covariance will be greater than the F value computed for the analysis of variance on the dependent variable. Winer *et al.* (1991) note that the higher the value of r_{WG} , the lower the value of the error term that will be computed for the analysis of covariance relative to value of the error term that will be computed if an analysis of variance is conducted on the dependent variable. Thus, the greater the absolute value of r_{WG} , the greater the precision of the analysis of covariance.

Computing the adjusted group/treatment means The analysis of covariance is an analysis of any variability on the dependent variable that is not accounted for by the covariate. If the result of the analysis of covariance is significant, it indicates that two or more treatment means differ significantly from one another. However, prior to comparing treatment means it is necessary that the latter values be adjusted for the effects of the covariate. In computing the adjusted treatment means, we are determining what the scores on the dependent variable would be if the groups did not differ on the covariate. Maxwell and Delaney (1990, p. 378) note that the adjusted treatment means on the dependent variable can be viewed as estimates of the values that would be obtained if the mean of the covariate for each of the groups was equal to mean of all N subjects on the covariate.

Equation 21.68 is the general equation for computing an adjusted treatment/group mean.

$$\bar{Y}'_j = \bar{Y}_j - b_{WG}(\bar{X}_j - \bar{X}_T) \quad (\text{Equation 21.68})$$

In Equation 21.68, the adjusted mean on the dependent variable for the j^{th} group is represented by the notation \bar{Y}'_j . The notation \bar{Y}_j is the unadjusted mean for the j^{th} group on the dependent variable (i.e., in the case of Example 21.5, the unadjusted means are the \bar{Y}_j values in Table 21.11 which are the same as the group means computed for Example 21.1). Thus, $\bar{Y}_1 = 9.2$, $\bar{Y}_2 = 6.6$, and $\bar{Y}_3 = 6.2$. The value \bar{X}_j represents the mean of the j^{th} group on the covariate. Thus, as noted in Table 21.11, $\bar{X}_1 = 15.2$, $\bar{X}_2 = 15.8$, and $\bar{X}_3 = 15.8$. The value \bar{X}_T is the mean of the $N = 15$ subjects on the covariate. Thus, $\bar{X}_T = (\sum X_1 + \sum X_2 + \sum X_3)/15 = (76 + 79 + 79)/15 = 15.6$. The value b_{WG} , which is referred to as the **within-groups regression coefficient**, is computed with either Equation 21.69 or Equation 21.70. For Example 21.5, the value $b_{WG} = 1.18$ is computed.⁷¹

$$b_{WG} = \frac{SP_{WG(XY)}}{SS_{WG(X)}} = \frac{14.6}{12.4} = 1.18 \quad (\text{Equation 21.69})$$

$$b_{WG} = r_{WG} \sqrt{\frac{MS_{WG(Y)}}{MS_{WG(X)}}} = .868 \sqrt{\frac{1.90}{1.03}} = 1.18 \quad (\text{Equation 21.70})$$

The adjusted group means are computed for the $k = 3$ groups below.

$$\bar{Y}'_1 = 9.2 - 1.18(15.2 - 15.6) = 9.672$$

$$\bar{Y}'_2 = 6.6 - 1.18(15.8 - 15.6) = 6.364$$

$$\bar{Y}'_3 = 6.2 - 1.18(15.8 - 15.6) = 5.964$$

Conducting comparisons among the adjusted group/treatment means The same types of comparisons for contrasting group means on the dependent variable that are described in Section VI can be employed in contrasting the adjusted group means. Visual inspection of the adjusted and unadjusted group means reveals that in the case of Groups 1 and 2 the adjusted means for the latter groups are further removed from one another than the unadjusted means. Employing the same protocol used in Section VI, the **planned simple comparison** on the adjusted means of Groups 1 and 2 is summarized in Table 21.15. The test statistic is then computed employing the appropriate equations presented in Section VI. Note that in the latter equations, the notation appropriate for comparing the adjusted mean values is substituted for the notation employed in Section VI.

Table 21.15 Planned Simple Comparison: Group 1 Versus Group 2

Group	\bar{Y}'_j	Coefficient (c_j)	Product ($c_j)(\bar{Y}'_j)$	Squared Coefficient (c_j) ²
1	9.672	+1	(+1)(9.672) = +9.672	1
2	6.364	-1	(-1)(6.364) = -6.364	1
3	5.964	0	(0)(5.964) = 0	0
		$\sum(c_j) = 0$	$\sum(c_j)(\bar{Y}'_j) = 3.308$	$\sum c_j^2 = 2$

Equation 21.17 is employed to compute the value $SS_{\text{comp(adj)}} = 27.36$.

$$SS_{\text{comp(adj)}} = \frac{n[\sum(c_j)(\bar{Y}_j')]^2}{\sum c_j^2} = \frac{5(3.308)^2}{2} = 27.36$$

Equation 21.18 is employed to compute the value $MS_{\text{comp(adj)}} = 27.36$.

$$MS_{\text{comp(adj)}} = \frac{SS_{\text{comp(adj)}}}{df_{\text{comp}}} = \frac{27.36}{1} = 27.36$$

The test statistic F_{comp} is computed with Equation 21.72. Keppel (1990) notes that instead of employing $MS_{WG(\text{adj})}$ as the denominator in Equation 21.72, the value computed with Equation 21.71 for MS'_{WG} should be employed.⁷²

(Equation 21.71)

$$MS'_{WG} = MS_{WG(\text{adj})} \left[1 + \frac{MS_{BG(X)}}{SS_{WG(X)}} \right] = .51 \left[1 + \frac{.6}{12.4} \right] = .535$$

$$F_{\text{comp(adj)}} = \frac{MS_{\text{comp(adj)}}}{MS'_{WG}} = \frac{27.36}{.535} = 51.14 \quad (\text{Equation 21.72})$$

Substituting $MS'_{WG} = .535$ in Equation 21.72, the value $F_{\text{comp(adj)}} = 51.14$ is computed. The numerator and denominator degrees of freedom employed for evaluating the computed F value for the comparison are $df_{\text{num}} = 1$ (since it is a single degree of freedom comparison), and $df_{\text{den}} = df_{WG(\text{adj})} = 11$. In **Table A10**, for $df_{\text{num}} = 1$ and $df_{\text{den}} = 11$, the tabled $F_{.95}$ and $F_{.99}$ values are $F_{.05} = 4.84$ and $F_{.01} = 9.65$. Since $F_{\text{comp(adj)}} = 51.14$ is greater than $F_{.05} = 4.84$ and $F_{.01} = 9.65$, the alternative hypothesis is supported at both the .05 and .01 levels. In other words, we can conclude that there is a significant difference between the adjusted means of Groups 1 and 2. Note how much larger the value $F_{\text{comp(adj)}} = 51.14$ is than the value $F_{\text{comp}} = 8.89$ computed for the unadjusted Group 1 versus Group 2 comparison in Section VI.

Equations 21.30 and 21.31 (which are employed for **Tukey's HSD test**) will be used to illustrate an **unplanned comparison** on the adjusted means of Groups 1 and 2. When Equation 21.30 is employed, the value $q = 10.12$ is computed.

$$q = \frac{\bar{Y}'_1 - \bar{Y}'_2}{\sqrt{\frac{MS'_{WG}}{n}}} = \frac{9.672 - 6.364}{\sqrt{\frac{.535}{5}}} = 10.12$$

The obtained value $q = 10.12$ is evaluated with **Table A13**. In the latter table, for the prespecified probability level, we locate the q value that is in the cell which is the intersection of the column for $k = 3$ means (which represents the total number of groups upon which the omnibus F value for the analysis of covariance is based), and the row for $df_{\text{error}} = 11$ (which represents the value $df_{WG(\text{adj})} = 11$ computed for the analysis of covariance). The tabled critical $q_{.05}$ and $q_{.01}$ values for $k = 3$ means and $df_{\text{error}} = 11$ are $q_{.05} = 3.82$ and $q_{.01} = 5.15$. Since the obtained value $q = 10.12$ is greater than the aforementioned tabled critical two-tailed values, the nondirectional alternative hypothesis $H_1: \mu'_1 \neq \mu'_2$ is supported at both the .05 and .01 levels. Note that when the unadjusted means of Group 1 and 2 are evaluated with **Tukey's HSD test** in Section VI, the alternative hypothesis is only supported at the .05 level.

When Equation 21.31 is employed to compute the minimum required difference (CD_{HSD}), in order for two means to differ significantly from one another at a prespecified level of significance, the CD_{HSD} value computed for the adjusted means is less than the value computed in Section VI for the unadjusted means. It is demonstrated below that the value $CD_{\text{HSD}} = 1.25$ computed at the .05 level for the adjusted means is less than the value $CD_{\text{HSD}} = 2.32$ computed in Section VI for the unadjusted means. It should be emphasized, however, that employing a covariate in and of itself does not guarantee a more sensitive analysis. The increased sensitivity of the analysis in the case of Example 21.5 is the result of the covariate having a substantial linear relationship with the dependent variable.

$$CD_{\text{HSD}} = q_{.05} \sqrt{\frac{MS'_{\text{WG}}}{n}} = (3.82) \sqrt{\frac{.535}{5}} = 1.25$$

Additional procedures that can be employed for conducting comparisons for an analysis of covariance can be found in Kirk (1995) and Winer *et al.* (1991).

Evaluation of the homogeneity of regression assumption The **homogeneity of regression assumption** of the analysis of covariance is that within each of the k groups there is a linear correlation between the dependent variable and the covariate, and that the k group regression lines have the same slope (i.e., are parallel to one another). A full discussion of the concept of linear regression and the procedure for determining the slope of a regression line can be found in Section VI of the **Pearson product-moment correlation coefficient**. The reader who is unfamiliar with the concept of regression is advised to review the latter discussion before continuing this section.

In order to evaluate the homogeneity of regression assumption, the following null and alternative hypotheses (which are evaluated with Equation 21.74) are employed. (The notation β_j in the null hypothesis represents the slope of the regression line of Y on X for the j^{th} group.)

Null hypothesis $H_0: \beta_1 = \beta_2 = \beta_3$

(In the underlying populations represented by the three groups, the slope of the regression line of Y on X for Group 1 equals the slope of the regression line of Y on X for Group 2 equals the slope of the regression line of Y on X for Group 3.)

Alternative hypothesis $H_1: \text{Not } H_0$

(This indicates there is a difference between the slopes of at least two of the $k = 3$ regression lines. In order to reject the null hypothesis, the F value computed with Equation 21.74 must be equal to or greater than the tabled critical F value at the prespecified level of significance.)

If the test of the homogeneity of regression assumption results in rejection of the null hypothesis, it means that the assumption is violated. Hinkle *et al.* (1998) and Tabachnick and Fidell (1996) note that if the null hypothesis for the homogeneity of regression assumption is rejected, it suggests that an interaction is present with regard to the relationship between the covariate and the dependent variable. The presence of an interaction means that the relationship between the covariate and the dependent variable is not consistent across the different treatments/groups. Consequently, a different adjustment will be required for each of the treatment means — in other words, Equation 21.68 cannot be employed to compute the adjusted means for each of the groups. Although Keppel (1991, p. 317) cites studies which suggest that the analysis of covariance is reasonably robust with respect to violation of the homogeneity of regression

assumption, other sources argue that violation of the assumption can seriously compromise the reliability of the analysis of covariance.

Equations 21.73 and 21.74 are employed to evaluate the homogeneity of regression assumption. Through use of Equation 21.73, a **within-groups regression sum of squares** (which is explained in Endnote 73) is computed. The latter value is then employed in Equation 21.74 to compute the test statistic.

$$SS_{wgreg} = \sum_{j=1}^k \left[SS_{Y_j} (1 - r_{j(XY)}^2) \right] \quad \text{(Equation 21.73)}$$

Where: $SS_{Y_j} = \sum Y_j^2 - [(\sum Y_j)^2 / n_j]$. The latter value indicates that the sum of squares for the Y variable (the dependent variable) is computed for each group.
 $r_{j(XY)}^2$ is the square of the correlation between the X variable (the covariate) and the Y variable (the dependent variable) within the j^{th} group.

The notation in Equation 21.73 indicates that for each group, the square of the correlation between the covariate and dependent variable is subtracted from 1, and the difference is multiplied by the sum of squares for the Y variable within that group. The value SS_{wgreg} is the sum of the values computed for the k groups.

The values $r_{1(XY)} = 1$, $r_{2(XY)} = .843$, and $r_{3(XY)} = .861$ are computed for each group by employing in Equation 28.1 the appropriate summary values for the five X and Y scores for that group, or through use of the equation $r = SP_{j(XY)} / \sqrt{SS_{X_j} SS_{Y_j}}$ (which is another way of expressing Equation 28.1). Employing the relevant summary values in Table 21.11, the three $r_{j(XY)}$ values are computed:

$$r_{1(XY)} = SP_{1(XY)} / \sqrt{SS_{X_1} SS_{Y_1}} = 2.8 / \sqrt{(2.8)(2.8)} = 1$$

$$r_{2(XY)} = SP_{2(XY)} / \sqrt{SS_{X_2} SS_{Y_2}} = 5.6 / \sqrt{(4.8)(9.2)} = .843$$

$$r_{3(XY)} = SP_{3(XY)} / \sqrt{SS_{X_3} SS_{Y_3}} = 6.2 / \sqrt{(4.8)(10.8)} = .861$$

Employing Equation 21.73, the value $SS_{wgreg} = 5.46$ is computed below.

$$\begin{aligned} SS_{wgreg} &= \left[\left(426 - \frac{(46)^2}{5} \right) (1 - (1)^2) \right] + \left[\left(227 - \frac{(33)^2}{5} \right) (1 - (.843)^2) \right] \\ &\quad + \left[\left(203 - \frac{(31)^2}{5} \right) (1 - (.861)^2) \right] = 5.46 \end{aligned}$$

Equation 21.74 is employed to compute the test statistic for the homogeneity of regression assumption. Two forms of the latter equation are presented below.

(Equation 21.74)

$$F = \frac{(SS_{WG(adj)} - SS_{wgreg}) / (k - 1)}{SS_{wgreg} / k(n_j - 2)} = \frac{k(n_j - 2)(SS_{WG(adj)} - SS_{wgreg})}{(k - 1)SS_{wgreg}}$$

Employing Equation 21.74, the value $F = .124$ is computed.

$$F = \frac{(5.61 - 5.46)/(3 - 1)}{5.46/[(3)(5 - 2)]} = \frac{3(5 - 2)(5.61 - 5.46)}{(3 - 1)5.46} = .124$$

The obtained value $F = .124$ is evaluated with [Table A10](#), employing as the numerator and denominator degrees of freedom $df_{\text{num}} = k - 1 = 2$ and $df_{\text{den}} = k(n_j - 2) = 9$. For $df_{\text{num}} = 2$ and $df_{\text{den}} = 9$, the tabled $F_{.95}$ and $F_{.99}$ values are $F_{.05} = 4.26$ and $F_{.01} = 8.02$. In order to reject the null hypothesis, the obtained F value must be equal to or greater than the tabled critical value at the prespecified level of significance. Since $F = .124$ is less than $F_{.05} = 4.26$, the null hypothesis cannot be rejected. Thus, we can conclude that the three regression lines are homogeneous.⁷³

Estimating the magnitude of treatment effect for the single-factor between-subjects analysis of covariance Values for the **omega squared** and **eta squared** statistics and **Cohen's f index** computed in Section VI can also be computed for the **single-factor between-subjects analysis of covariance**. The appropriate adjusted values from the analysis of covariance can be substituted in any of the Equations 21.41–21.47. Through use of Equations 21.41, 21.43, and 21.45, the values of **omega squared**, **eta squared**, and **Cohen's f index** are computed for the analysis of covariance. Notice that the computed values $\hat{\omega}^2 = .84$, $\hat{\eta}^2 = .87$, and $f = 2.29$ are substantially larger than the analogous values computed for the magnitude of the treatment effect for the analysis of variance. The latter reflects the fact that when the data are adjusted for the effects of the covariate, a substantially larger proportion of the variability on the dependent variable is associated with the independent variable.

$$\hat{\omega}_{\text{adj}}^2 = \frac{SS_{BG(\text{adj})} - (k - 1)MS_{WG(\text{adj})}}{SS_{T(\text{adj})} + MS_{WG(\text{adj})}} = \frac{37.76 - (3 - 1)(.51)}{43.37 + .51} = .84$$

$$\hat{\eta}^2 = \frac{SS_{BG(\text{adj})}}{SS_{T(\text{adj})}} = \frac{37.76}{43.37} = .87$$

$$f = \sqrt{\frac{\hat{\omega}^2}{1 - \hat{\omega}^2}} = \sqrt{\frac{.84}{1 - .84}} = 2.29$$

Computation of the power of the single-factor between-subjects analysis of covariance Equation 21.38, which is employed to compute the power of the **single-factor between-subjects analysis of variance**, can also be used to compute the power of the **single-factor between-subjects analysis of covariance**. The value $\sigma_{WG(\text{adj})}^2$ is employed in Equation 21.38 in place of σ_{WG}^2 . If prior data are available from previous studies, the value of $MS_{WG(\text{adj})}$ in such studies can be used as an estimate of $\sigma_{WG(\text{adj})}^2$. Cohen (1977, 1988) and Keppel (1991) discusses power computations for the analysis of covariance in more detail.

Final remarks on the analysis of covariance In closing the discussion of analysis of covariance, it should be emphasized that the procedure should not be used indiscriminately, since a considerable investment of time and effort is required to obtain subjects' scores on a covariate, as well as the fact that the analysis requires laborious computations (although admittedly, the latter will not be an issue if one has access to the appropriate computer software). Kirk (1995, p. 710) suggests the following with regard to determining the appropriateness of employing an analysis of covariance: a) If a researcher is aware of one or more extraneous variables which cannot be controlled experimentally that may influence the dependent variable, they can be

employed as covariates; and b) The measures obtained for the covariate(s) should not be influenced by the experimental treatments under study. The latter condition will be met if any of the following is true: 1) The measures of the covariate are obtained prior to introducing the experimental treatment; 2) The measures of the covariate are obtained after the introduction of the experimental treatment, but before the treatment can have an impact on the covariate; and 3) Based on prior information, the researcher can assume the covariate is unaffected by the experimental treatment. In such a case, the covariate can be measured after the administration of the experimental treatment.

Winer *et al.* (1991, pp. 787–788) discuss the advantages and disadvantages of employing an analysis of covariance versus the use of a factorial design in which the covariate is employed as a second independent variable. Factorial designs are discussed in detail in the discussion of the **between-subjects factorial analysis of variance (Test 27)**. Winer *et al.* (1991) note that one advantage of employing a factorial design (which is evaluated with the appropriate factorial analysis of variance) is that its assumptions are less restrictive than the assumptions for an analysis of covariance.⁷⁴ Disadvantages associated with a factorial design are that small and/or unequal sample sizes may be present within the different levels of the factors, unless the total size of the sample is relatively large. Keppel (1991, p. 326) and Kirk (1995, p. 739) discuss the pros and cons of employing stratification/blocking, and then conducting the appropriate analysis of variance as an alternative to the analysis of covariance. Stratification involves employing the covariate to form homogeneous blocks of subjects, in order to reduce the measure of error variability employed in computing the *F* ratio. The subject of blocking is discussed in Section I of the **single-factor within-subjects analysis of variance (Test 24)**.

For a more detailed discussion of analysis of covariance the reader should consult such sources as Hinkel *et al.* (1998), Keppel (1991), Keppel and Zedeck (1989), Kirk (1995), Marascuilo and Levin (1983), Marascuilo and Serlin (1988), Maxwell and Delaney (1990), Myers and Well (1995), Tabachnick and Fidell (1996), and Winer *et al.* (1991).

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Endnotes

1. The term **single-factor** refers to the fact that the design upon which the analysis of variance is based involves a single independent variable. Since factor and independent variable mean the same thing, **multifactor designs** (more commonly called **factorial designs**) that are evaluated with the analysis of variance involve more than one independent variable. Multifactor analysis of variance procedures are discussed under the **between-subjects factorial analysis of variance**.
2. It should be noted that if an experiment is confounded, one cannot conclude that a significant portion of **between-groups variability** is attributed to the independent variable. This is the case, since if one or more confounding variables systematically vary with the levels of the independent variable, a significant difference can be due to a confounding variable rather than the independent variable.
3. The homogeneity of variance assumption is also discussed in Section VI of the **t test for two independent samples** in reference to a design involving two independent samples.
4. Although it is possible to conduct a directional analysis, such an analysis will not be described with respect to the analysis of variance. A discussion of a directional analysis

when $k = 2$ can be found under the ***t* test for two independent samples**. In addition, a discussion of one-tailed F values can be found in Section VI of the latter test under the discussion of the **Hartley's F_{\max} test for homogeneity of variance/ F test for two population variances**. A discussion of the evaluation of a directional alternative hypothesis when $k \geq 3$ can be found in Section VII of the **chi-square goodness-of-fit test (Test 8)**. Although the latter discussion is in reference to analysis of a k independent samples design involving categorical data, the general principles regarding the analysis of a directional alternative hypothesis when $k \geq 3$ are applicable to the analysis of variance.

5. Some sources present an alternative method for computing SS_{BG} when the number of subjects in each group is not equal. Whereas Equation 21.3 weighs each group's contribution based on the number of subjects in the group, the alternative method (which is not generally recommended) weighs each group's contribution equally, irrespective of sample size. Keppel (1991), who describes the latter method, notes that as a general rule the value it computes for SS_{BG} is close to the value obtained with Equation 21.3, except when the sample sizes of the groups differ substantially from one another.
6. Since there are an equal number of subjects in each group, the Equation for SS_{BG} can also be written as follows:

$$SS_{BG} = \frac{[(46)^2 + (33)^2 + (31)^2]}{5} - \frac{(110)^2}{15} = 26.53$$

7. SS_{WG} can also be computed with the following equation:

$$SS_{WG} = \sum X_T^2 - \sum_{j=1}^k \left[\frac{(\sum X_j)^2}{n_j} \right] = 856 - \left[\frac{(46)^2}{5} + \frac{(33)^2}{5} + \frac{(31)^2}{5} \right] = 22.80$$

Since there are an equal number of subjects in each group, n can be used in place of n_j in the above equation, as well as in Equation 21.5. The numerators of the term in the brackets can be combined and written over a single denominator that equals the value $n = 5$.

8. When $n_1 = n_2 = n_3$, $MS_{WG} = (\bar{s}_1^2 + \bar{s}_2^2 + \bar{s}_3^2)/k$. Thus, since $\bar{s}_1^2 = .7$, $\bar{s}_2^2 = 2.3$, and $\bar{s}_3^2 = 2.7$, $MS_{WG} = (.7 + 2.3 + 2.7)/3 = 1.9$.
9. Equation 21.9 can be employed if there are an equal or unequal number of subjects in each group. The following equation can also be employed when the number of subjects in each group is equal or unequal: $df_{WG} = (n_1 - 1) + (n_2 - 1) + \cdots + (n_k - 1)$. The equation $df_{WG} = k(n - 1) = nk - k$ can be employed to compute df_{WG} , but only when the number of subjects in each group is equal.
10. When there are an equal number of subjects in each group, since $N = nk$, $df_T = nk - 1$.
11. There is a separate F distribution for each combination of df_{num} and df_{den} values. [Figure 21.2](#) depicts the F distribution for three different sets of degrees of freedom values. Note that in each of the distributions, 5% of the distribution falls to the right of the tabled critical $F_{.05}$ value.

Most tables of the F distribution do not include tabled critical values for all possible values of df_{num} and df_{den} . The protocol that is generally employed for determining a critical

F value for a df value that is not listed is to either employ interpolation or to employ the value closest to the desired df value. Some sources qualify the latter by stating that in order to insure that the Type I error rate does not exceed the prespecified value of alpha, one should employ the df value that is closest to but not above the desired df value.

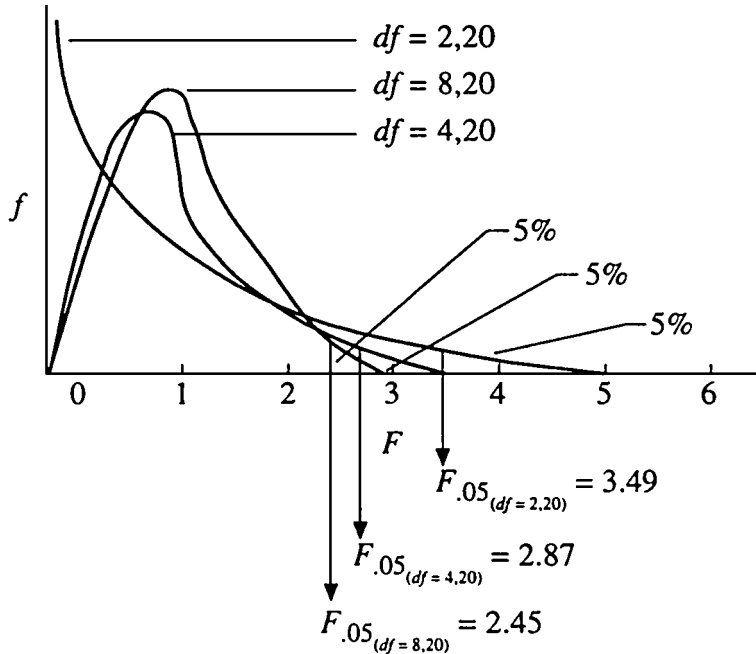


Figure 21.2 Representative F Distributions for Different df Values

12. Although the discussion of comparison procedures in this section will be limited to the analysis of variance, the underlying general philosophy can be generalized to any inferential statistical test for which comparisons are conducted.
13. The terms **family** and **set** are employed synonymously throughout this discussion.
14. The accuracy of Equation 21.13 will be compromised if all of the comparisons are not independent of one another. Independent comparisons, which are commonly referred to as **orthogonal comparisons**, are discussed later in the section.
15. Equation 21.14 tends to overestimate the value of α_{FW} . The degree to which it overestimates α_{FW} increases as either the value of c or α_{PC} increase. For larger values of c and α_{PC} , Equation 21.14 is not very accurate.
16. Equation 21.16 provides a computationally quick approximation of the value computed with Equation 21.15. The value computed with Equation 21.16 tends to underestimate the value of α_{PC} . The larger the value of α_{FW} or c , the greater the degree α_{PC} will be underestimated with the latter equation. When $\alpha = .05$, however, the two equations yield values that are almost identical.
17. This example is based on a discussion of this issue in Howell (1992, 1997) and Maxwell and Delaney (1990).

18. The term **single degree of freedom comparison** reflects the fact that $k = 2$ means are contrasted with one another. Although one or both the $k = 2$ means may be a composite mean that is based on the combined scores of two or more groups, any composite mean is expressed as a single mean value. The latter is reflected in the fact that there will always one equals sign (=) in the null hypothesis for a single degree of freedom comparison.
19. Although the examples illustrating comparisons will assume a nondirectional alternative hypothesis, the alternative hypothesis can also be stated directionally. When the alternative hypothesis is stated directionally, the tabled critical one-tailed F value must be employed. Specifically, when using the F distribution in evaluating a directional alternative hypothesis, when $\alpha_{PC} = .05$, the tabled $F_{.90}$ value is employed for the one-tailed $F_{.05}$ value instead of the tabled $F_{.95}$ value (which as noted earlier is employed for the two-tailed/nondirectional $F_{.05}$ value). When $\alpha_{PC} = .01$, the tabled $F_{.98}$ value is employed for the one-tailed $F_{.01}$ value instead of the tabled $F_{.99}$ value (which is employed for the two-tailed/nondirectional $F_{.01}$ value).
20. If the coefficients of Groups 1 and 2 are reversed (i.e., $c_1 = -1$ and $c_2 = +1$), the value of $\sum(c_j)(\bar{X}_j)$ will equal -2.6 . The fact that the sign of the latter value is negative will not affect the test statistic for the comparison. This is the case, since, in computing the F value for the comparison, the value $\sum(c_j)(\bar{X}_j)$ is squared and, consequently, it becomes irrelevant whether $\sum(c_j)(\bar{X}_j)$ is a positive or negative number.
21. When the sample sizes of all k groups are not equal, the value of the **harmonic mean** (which is discussed in Section VI of the **t test for two independent samples**) is employed to represent n in Equation 21.17. However, when the harmonic mean is employed, if there are large discrepancies between the sizes of the samples, the accuracy of the analysis may be compromised.
22. MS_{WG} is employed as the estimate of error variability for the comparison, since, if the homogeneity of variance assumption is not violated, the pooled within-groups variability employed in computing the omnibus F value will provide the most accurate estimate of error variability.
23. As is the case with simple comparisons, the alternative hypothesis for a complex planned comparison can also be evaluated nondirectionally.
24. A reciprocal of a number is the value 1 divided by that number.
25. When there are an equal number of subjects in each group it is possible, though rarely done, to assign different coefficients to two or more groups on the same side of the equals sign. In such an instance the composite mean reflects an unequal weighting of the groups. On the other hand, when there are an unequal number of subjects in any of the groups on the same side of the equals sign, any groups that do not have the same sample size will be assigned a different coefficient. The coefficient a group is assigned will reflect the proportion it contributes to the total number of subjects on that side of the equals sign. Thus, if Groups 1 and 2 are compared with Group 3, and there are 4 subjects in Group 1 and 6 subjects in Group 2, there are a total of 10 subjects involved on that side of the equals sign. The absolute value of the coefficient assigned to Group 1 will be $\frac{4}{10} = \frac{2}{5}$, whereas the absolute value assigned to Group 2 will be $\frac{6}{10} = \frac{3}{5}$.

26. When any of the coefficients are fractions, in order to simplify calculations some sources prefer to convert the coefficients into integers. In order to do this, each coefficient must be multiplied by a **least common denominator**. A least common denominator is the smallest number (excluding 1) that is divisible by all of the denominators of the coefficients. With respect to the complex comparison under discussion, the least common denominator is 2, since 2 is the smallest number that can be divided by 1 and 2 (which are the denominators of the coefficients $1/1 = 1$ and $1/2$). If all of the coefficients are multiplied by 2, the coefficients are converted into the following values: $c_1 = -1$, $c_2 = -1$, $c_3 = +2$. If the latter coefficients are employed in the calculations that follow, they will produce the same end result as that obtained through use of the coefficients employed in Table 21.4. It should be noted, however, that if the converted coefficients are employed, the value $\Sigma(c_j)(\bar{X}_j) = -1.7$ in Table 21.4 will become twice the value that is presently listed (i.e., it becomes 3.4). As a result of this, $\Sigma(c_j)(\bar{X}_j)$ will no longer represent the difference between the two sets of means contrasted in the null hypothesis. Instead, it will be a multiple of that value — specifically, the multiple of the value by which the coefficients are multiplied.
27. If $n_a \neq n_b$, $\sqrt{(MS_{WG}/n_a) + (MS_{WG}/n_b)}$ is employed as the denominator of Equation 21.22 and $\sqrt{[(\Sigma c_a^2)(MS_{WG})/n_a] + [(\Sigma c_b^2)(MS_{WG})/n_b]}$ is employed as the denominator of Equation 21.23.
28. If the value $\sqrt{(\bar{s}_a^2/n_a) + (\bar{s}_b^2/n_b)}$ is employed as the denominator of Equations 21.22/21.23, or if the degrees of freedom for Equations 21.22/21.23 are computed with Equation 11.4 ($df = n_a + n_b - 2$), a different result will be obtained since: a) Unless the variance for all of the groups is equal, it is unlikely that the computed t value will be identical to the one computed with Equations 21.22/21.23; and b) If $df = n_a + n_b - 2$ is used, the tabled critical t value employed will be higher than the tabled critical value employed for Equations 21.22/21.23. This is the case, since the df value associated with MS_{WG} is larger than the df value associated with $df = n_a + n_b - 2$. The larger the value of df , the lower the corresponding tabled critical t value.
29. Equations 21.24 and 21.25 are, respectively, derived from Equations 21.22 and 21.23. When two groups are compared with one another, the data may be evaluated with either the t distribution or the F distribution. The relationship between the two distributions is $F = t^2$. In view of this, the term $\sqrt{F_{(1, WG)}}$ in Equations 21.24 and 21.25 can also be written as $t_{df_{WG}}$. In other words, Equation 21.24 can be written as $CD_{LSD} = t_{df_{WG}} \sqrt{(2MS_{WG})/n}$ (and, in the case of Equation 21.25, the same equation is employed, except for the fact that, inside the radical, (Σc_j^2) is employed in place of 2). Thus, in the computations to follow, if a nondirectional alternative hypothesis is employed with $\alpha = .05$, one can employ either $F_{.05} = 4.75$ (for $df_{num} = 1$, $df_{den} = 12$) or $t_{.05} = 2.18$ (for $df = 12$), since $(t_{.05} = 2.18)^2 = (F_{.05} = 4.75)$.
30. As is noted in reference to **linear contrasts**, the $df = 1$ value for the numerator of the F ratio for a single degree of freedom comparison is based on the fact that the comparison involves $k = 2$ groups with $df = k - 1$. In the same respect, in the case of **complex comparisons** there are two sets of means, and thus $df = k_{comp} - 1$.
31. As indicated in Endnote 29, if a t value is substituted in Equation 21.24 it will yield the

same result. Thus, if $t_{.05} = 2.18$ is employed in the equation $CD_{LSD} = t_{df_{wg}}\sqrt{(2MS_{wg})/n}$, $CD_{LSD} = 2.18\sqrt{[(2)(1.9)]/5} = 1.90$.

32. The absolute value of t is employed, since a nondirectional alternative hypothesis is evaluated.
33. When $n_1 \neq n_2$, $\sqrt{(MS_{wg}/n_a) + (MS_{wg}/n_b)}$ is employed in Equation 21.26 in place of $\sqrt{(2MS_{wg})/n}$.
34. Since, in a two-tailed analysis we are interested in a proportion that corresponds to the most extreme .0167 cases in the distribution, one-half of the cases (i.e., .0083) falls in each tail of the distribution.
35. The only exception to this will be when one comparison is being made (i.e., $c = 1$), in which case both methods yield the identical CD value.
36. Some sources employ the abbreviation **WSD** for **wholly significant difference** instead of **HSD**.
37. The value of α_{FW} for **Tukey's HSD test** is compared with the value of α_{FW} for other comparison procedures within the framework of the discussion of the **Scheffé test** later in this section.
38. When the tabled critical q value for $k = 2$ treatments is employed, the **Studentized range statistic** will produce equivalent results to those obtained with **multiple t tests/Fisher's LSD test**. This will be demonstrated later in reference to the **Newman-Keuls test**, which is another comparison procedure that employs the **Studentized range statistic**.
39. As is the case with a t value, the sign of q will only be relevant if a directional alternative hypothesis is evaluated. When a directional alternative hypothesis is evaluated, in order to reject the null hypothesis, the sign of the computed q value must be in the predicted direction, and the absolute value of q must be equal to or greater than the tabled critical q value at the prespecified level of significance.
40. Although Equations 21.30 and 21.31 can be employed for both simple and complex comparisons, sources generally agree that **Tukey's HSD test** should only be employed for simple comparisons. Its use with only simple comparisons is based on the fact that in the case of complex comparisons it provides an even less powerful test of an alternative hypothesis than does the **Scheffé test** (which is an extremely conservative procedure) discussed later in this section.
41. When $n_a \neq n_b$ and/or the homogeneity of variance assumption is violated, some sources recommend using the following modified form of Equation 21.31 (referred to as the **Tukey-Kramer procedure**) for computing CD_{HSD} : $CD_{HSD} = q_{(k, df_{wg})}\sqrt{MS_{wg}[(1/n_a) + (1/n_b)]/2}$. Other sources, however, do not endorse the use of the latter equation and provide alternative approaches for dealing with unequal sample sizes.

In the case of unequal sample sizes, some sources (e.g., Winer *et al.*, 1991) recommend employing the **harmonic mean** of the sample sizes to compute the value of n for Equations 21.30 and 21.31 (especially if the sample sizes are approximately the same

value). The harmonic mean is described in Section VI of the ***t* test for two independent samples**.

42. The only comparison for which the minimum required difference computed for the **Newman-Keuls test** will equal CD_{HSD} will be the comparison contrasting the smallest and largest means in the set of k means. One exception to this is a case in which two or more treatments have the identical mean value, and that value is either the lowest or highest of the treatment means. Although the author has not seen such a configuration discussed in the literature, one can argue that in such an instance the number of steps between the lowest and highest mean should be some value less than k . One can conceptualize all cases of a tie as constituting one step, or perhaps, for those means that are tied, one might employ the average of the steps that would be involved if all those means are counted as separate steps. The larger the step value that is employed, the more conservative the test.
43. If Equation 21.30 is employed, it uses the same values that are employed for **Tukey's HSD test**, and thus yields the identical q value. Thus, $q = (9.2 - 6.6)/\sqrt{1.9/5} = 4.22$.
44. One exception to this involving the **Bonferroni-Dunn test** will be discussed later in this section.
45. Recollect that the **Bonferroni-Dunn test** assumed that a total of 6 comparisons are conducted (3 simple comparisons and 3 complex comparisons). Thus, as noted earlier, since the number of comparisons exceeds $[k(k - 1)]/2 = [3(3 - 1)]/2 = 3$, the **Scheffé test** will provide a more powerful test of an alternative hypothesis than the **Bonferroni-Dunn test**.
46. The author is indebted to Scott Maxwell for his input on the content of the discussion to follow.
47. Dunnett (1964) developed a modified test procedure (described in Winer *et al.*, (1991)) to be employed in the event that there is a lack of homogeneity of variance between the variance of the control group and the variance of the experimental groups with which it is contrasted.
48. The philosophy to be presented here can be generalized to any inferential statistical analysis.
49. Although the difference between $\alpha_{FW} = .05$ and $\alpha_{FW} = .10$ may seem trivial, a result that is declared significant is more likely to be submitted and/or accepted for publication.
50. The reader may find it useful to review the discussion of **effect size** in Section VI of the **single sample *t* test** and the ***t* test for two independent samples**. Effect size indices are also discussed in Section IX (the **Addendum**) of the **Pearson product-moment correlation coefficient** under the discussion of **meta-analysis and related topics**.
51. The reader may want to review the discussion of confidence intervals in Section VI of both the **single sample *t* test** and the ***t* test for two independent samples**.
52. The ***F* test for two population variances** (discussed in conjunction with the **F_{\max} test as Test 11a** in Section VI of the ***t* test for two independent samples**) can only be employed to evaluate the homogeneity of variance hypothesis when $k = 2$.

53. ϕ should not be confused with the **phi coefficient** (also represented by the notation ϕ), discussed under the **chi-square test for $r \times c$ tables (Test 16)**. Although the latter measure is identified by the same symbol, it represents a different measure than the noncentrality parameter.
54. If a power analysis is conducted after the analysis of variance, the value computed for MS_{WG} can be employed to represent σ_{WG}^2 if the researcher has reason to believe it is a reliable estimate of error/within-groups variability in the underlying population. If prior to conducting a study reliable data are available from other studies, the MS_{WG} values derived in the latter studies can be used as a basis for estimating σ_{WG}^2 .
55. When there is no curve that corresponds exactly to df_{WG} , one can either interpolate or employ the df_{WG} value closest to it.
56. Tiku (1967) has derived more detailed power tables that include the alpha values .025 and .005.
57. When $k = 2$, Equations 21.41/21.42 and Equation 11.14 will yield the same $\tilde{\omega}^2$ value.
58. The following should be noted with respect to the **eta squared** statistic: a) Earlier in this section it was noted that Cohen (1977; 1988, pp. 284–287) employs the values .0099, .0588, and .1379 as the lower limits for defining a small versus medium versus large effect size for the **omega squared** statistic. In actuality, Cohen (1977; 1988, pp. 284–287) employs the notation for **eta squared** (i.e., η^2) in reference to the aforementioned effect size values. However, the definition Cohen (1977; 1988, p. 281) provides for **eta squared** is identical to Equation 21.40 (which is the equation for **omega squared**). For the latter reason, various sources (e.g., Keppel (1991) and Kirk (1995)) employ the values .0099, .0588, and .1379 in reference to the **omega squared** statistic; b) Equation 21.44 (the equation for *Adjusted* $\tilde{\eta}^2$) is essentially equivalent to Equation 21.40 (the definitional equation for the population parameter **omega squared**); c) Some sources employ the notation R^2 for the **eta squared** statistic. The statistic represented by R^2 or $\tilde{\eta}^2$ is commonly referred to as the **correlation ratio**, which is the squared multiple correlation coefficient that is computed when multiple regression (discussed under the **multiple correlation coefficient (Test 28k)**) is employed to predict subjects' scores on the dependent variable based on group membership. The use of R^2 in this context reflects the fact that the analysis of variance can be conceptualized within the framework of a multiple regression model; d) When $k = 2$, the **eta squared statistic** is equivalent to r_{pb} , which represents the **point-biserial correlation coefficient (Test 28h)**. Under the discussion of r_{pb} the equivalency of $\tilde{\eta}^2$ and r_{pb} is demonstrated.
59. A number of different measures have been developed to determine the magnitude of treatment effect for comparison procedures. Unfortunately, researchers do not agree with respect to which of the available measures is most appropriate to employ. Keppel (1991) provides a comprehensive discussion of this subject.
60. Some sources employ $\sqrt{F_{(1, df_{WG})}}$ in Equation 21.48 instead of $t_{df_{WG}}$. Since $t = \sqrt{F}$, the two values produce equivalent results. The tabled critical two-tailed t value at a prespecified level of significance will be equivalent to the square root of the tabled critical F value at the same level of significance for $df_{num} = 1$ and $df_{den} = df_{WG}$.

61. In using Equation 2.7, s_1/\sqrt{n} is equivalent to $s_{\bar{X}_1}$.
62. In the interest of precision, Keppel and Zedeck (1989, p. 98) note that although when the null hypothesis is true, the median of the sampling distribution for the value of F equals 1, the mean of the sampling distribution of F is slightly above one. Specifically, the expected value of $F = df_{WG}/df_{(WG-2)}$. It should also be noted that although it rarely occurs, it is possible that $MS_{WG} > MS_{BG}$. In such a case the value of F will be less than 1 and, obviously, if $F < 1$, the result cannot be significant.
63. In employing double (or even more than two) summation signs such as $\sum_{j=1}^k \sum_{i=1}^n$, the mathematical operations specified are carried out beginning with the summation sign that is farthest to the right and continued sequentially with those operations specified by summation signs to the left. Specifically, if $k = 3$ and $n = 5$, the notation $\sum_{j=1}^k \sum_{i=1}^n X_{ij}$ indicates that the sum of the n scores in Group 1 are computed, after which the sum of the n scores in Group 2 are computed, after which the sum of the n scores in Group 3 are computed. The final result will be the sum of all the aforementioned values that have been computed.
64. For each of the $N = 15$ subjects in Table 21.9, the following is true with respect to the contribution of a subject's score to the total variability in the data:

$$(X_{ij} - \bar{X}_T) = (\bar{X}_j - \bar{X}_T) + (X_{ij} - \bar{X}_j)$$

Total deviation score = BG deviation score + WG deviation score

65. In evaluating a directional alternative hypothesis, when $k = 2$ the tabled $F_{.90}$ and $F_{.98}$ values (for the appropriate degrees of freedom) are, respectively, employed as the one-tailed .05 and .01 values. Since the values for $F_{.90}$ and $F_{.98}$ are not listed in Table A10, the values $F_{.90} = 3.46$ and $F_{.98} = 8.41$ can be obtained by squaring the tabled critical one-tailed values $t_{.05} = 1.86$ and $t_{.01} = 2.90$, by employing more extensive tables of the F distribution available in other sources, or through interpolation.
66. In the case of a factorial design it is also possible to have a **mixed-effects model**. In a **mixed-effects model** it is assumed that at least one of the independent variables is based on a fixed-effects model and that at least one is based on a random-effects model.
67. Winer *et al.* (1991) note that the **analysis of covariance** was originally presented by Fisher (1932).
68. The equations below are alternative equations that can be employed to compute the values $SS_{T(\text{adj})}$ and $SS_{WG(\text{adj})}$. The slight discrepancy in values is the result of rounding off error. The computation of the values r_T and r_{WG} are described at a later point in the discussion of the analysis of covariance.

$$SS_{T(\text{adj})} = SS_{T(Y)}(1 - r_T^2) = 49.33[1 - (.347)^2] = 43.39$$

$$SS_{WG(\text{adj})} = SS_{WG(Y)}(1 - r_{WG}^2) = 22.8[1 - (.868)^2] = 5.62$$

69. Through use of Equation 28.1, the sample correlation between the covariate and the

dependent variable is computed to be $r_T = .347$. In the computations below, N is employed to represent the total number of subjects (in lieu of n , which is employed in Equation 28.1). The values $\Sigma X_T^2 = 3664$ and $\Sigma Y_T^2 = 856$ are the sums of the ΣX_j^2 and ΣY_j^2 scores for the $k = 3$ groups.

$$r = \frac{\Sigma(XY)_T - \frac{(\Sigma X_T)(\Sigma Y_T)}{N}}{\sqrt{\left[\Sigma X_T^2 - \frac{(\Sigma X_T)^2}{N}\right]\left[\Sigma Y_T^2 - \frac{(\Sigma Y_T)^2}{N}\right]}} = \frac{1725 - \frac{(234)(110)}{15}}{\sqrt{\left[3664 - \frac{(234)^2}{15}\right]\left[856 - \frac{(110)^2}{15}\right]}} = .347$$

The value $r = .347$ can be computed through use of the equation $r = SP_{XY}/\sqrt{SS_X SS_Y}$ (which is discussed at the end of Section IV of the **Pearson product-moment correlation coefficient**). When the values $SP_{T(XY)} = 9$, $SS_{T(X)} = 13.6$, and $SS_{T(Y)} = 49.33$ (computed in the bottom of Table 21.11) are substituted in the latter equation, the resulting value is $r = 9/\sqrt{(13.6)(49.33)} = .347$.

70. The equation noted below is an alternative way of computing r_{WG} through use of the elements employed in Equation 28.1. The relevant values within each group are pooled in the numerator and denominator of the equation.

$$\begin{aligned} r &= \frac{\sum_{j=1}^k \left[\Sigma X_j Y_j - \frac{(\Sigma X_j)(\Sigma Y_j)}{n_j} \right]}{\sqrt{\sum_{j=1}^k \left[\Sigma X_j^2 - \frac{(\Sigma X_j)^2}{n_j} \right] \sum_{j=1}^k \left[\Sigma Y_j^2 - \frac{(\Sigma Y_j)^2}{n_j} \right]}} \\ &= \frac{\left[702 - \frac{(76)(46)}{5} \right] + \left[527 - \frac{(79)(33)}{5} \right] + \left[496 - \frac{(79)(31)}{5} \right]}{\sqrt{\left[\left[1158 - \frac{(76)^2}{5} \right] + \left[1253 - \frac{(79)^2}{5} \right] + \left[1253 - \frac{(79)^2}{5} \right] \right] \left[\left[426 - \frac{(46)^2}{5} \right] + \left[227 - \frac{(33)^2}{5} \right] + \left[203 - \frac{(31)^2}{5} \right] \right]}} \\ &= .868 \end{aligned}$$

71. If the homogeneity of regression assumption for the analysis of covariance is violated, the value computed for b_{WG} will result in biased adjusted mean values (i.e., the adjusted mean values for the groups will not be accurate estimates of their true values in the underlying populations). Evaluation of the homogeneity of variance assumption is discussed later in this section.

72. Equation 21.71 can also be written as follows:

$$MS_{WG}' = MS_{WG(adj)} + MS_{WG(adj)} \left[\frac{MS_{BG(X)}}{SS_{WG(X)}} \right] = .51 + .51 \left[\frac{.6}{12.4} \right] = .535$$

73. An alternative way to evaluate the homogeneity of regression assumption is presented by Keppel (1991, pp. 317–320), who notes that the **adjusted within-groups sum of squares** ($SS_{WG(adj)}$) can be broken down into the following two components: a) The **between-groups regression sum of squares** (SS_{bgreg}), which is a source of variability that represents the

degree to which the group regression coefficients deviate from the average regression coefficient for all of the data; and b) The **within-groups regression sum of squares** (SS_{wgreg}), which is a source of variability that represents the degree to which the scores of individual subjects deviate from the regression line of the group of which a subject is a member. Since $SS_{WG(adj)}$ is the sum of SS_{bgreg} and SS_{wgreg} , the value of SS_{bgreg} can be expressed as follows: $SS_{bgreg} = SS_{WG(adj)} - SS_{wgreg}$.

Although we have already computed the value of SS_{wgreg} , an alternative way to compute SS_{wgreg} is with the equation noted below.

$$SS_{wgreg} = \sum_{j=1}^k \left[SS_{Y_j} - \frac{(SP_{j(XY)})^2}{SS_{X_j}} \right]$$

The notation in the above equation indicates that within each group, the result of dividing the square of the sum of products (i.e., $SP_{j(XY)}$ is squared) by the sum of squares for the X variable/the covariate (SS_{X_j}) is subtracted from the sum of squares for the Y variable/the dependent variable (SS_{Y_j}). The resulting values for the $k = 3$ groups are then summed. The values for SS_{Y_j} , SS_{X_j} , and $SP_{j(XY)}$ are listed in Table 21.11 for each group at the bottom of the summary information for that group. The computation of SS_{wgreg} is demonstrated below.

$$SS_{wgreg} = \left[2.8 - \frac{(2.8)^2}{2.8} \right] + \left[9.2 - \frac{(5.6)^2}{4.8} \right] + \left[10.8 - \frac{(6.2)^2}{4.8} \right] = 5.46$$

Employing the values $SS_{WG(adj)} = 5.61$ and $SS_{wgreg} = 5.46$, we can compute that the value of $SS_{bgreg} = .15$.

$$SS_{bgreg} = SS_{WG(adj)} - SS_{wgreg} = 5.61 - 5.46 = .15$$

A mean square is computed for the between-groups regression element and the within-groups regression element as noted below. The degrees of freedom for the between-groups regression element is $df_{bgreg} = k - 1 = 3 - 1 = 2$, and the degrees of freedom for the within-groups regression element is $df_{wgreg} = k(n - 2) = 3(5 - 2) = 9$.

$$MS_{bgreg} = \frac{SS_{bgreg}}{df_{bgreg}} = \frac{.15}{2} = .075 \quad MS_{wgreg} = \frac{SS_{wgreg}}{df_{wgreg}} = \frac{5.46}{9} = .606$$

The F ratio for evaluating the homogeneity of regression assumption is computed with the equation below. The degrees of freedom employed in evaluating the F ratio are $df_{num} = df_{bgreg} = 2$ and $df_{den} = df_{wgreg} = 9$. For $df_{num} = 2$ and $df_{den} = 9$, the tabled $F_{.95}$ and $F_{.99}$ values are $F_{.05} = 4.26$ and $F_{.01} = 8.02$. Since $F = .124$ is less than $F_{.05} = 4.26$, the null hypothesis cannot be rejected. The result is identical to that obtained with the other method.

$$F = \frac{MS_{bgreg}}{MS_{wgreg}} = \frac{.075}{.606} = .124$$

74. In addition to the assumptions already noted for the analysis of covariance, it also has the usual assumptions for the analysis of variance (i.e., normality of the underlying population distributions and homogeneity of variance).

Test 22

The Kruskal–Wallis One-Way Analysis of Variance by Ranks (Nonparametric Test Employed with Ordinal Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test In a set of k independent samples (where $k \geq 2$), do at least two of the samples represent populations with different median values?

Relevant background information on test The **Kruskal–Wallis one-way analysis of variance by ranks** (Kruskal (1952) and Kruskal and Wallis (1952)) is employed with ordinal (rank-order) data in a hypothesis testing situation involving a design with two or more independent samples. The test is an extension of the **Mann–Whitney U test (Test 12)** to a design involving more than two independent samples and, when $k = 2$, the **Kruskal–Wallis one-way analysis of variance by ranks** will yield a result that is equivalent to that obtained with the **Mann–Whitney U test**. If the result of the **Kruskal–Wallis one-way analysis of variance by ranks** is significant, it indicates there is a significant difference between at least two of the sample medians in the set of k medians. As a result of the latter, the researcher can conclude there is a high likelihood that at least two of the samples represent populations with different median values.

In employing the **Kruskal–Wallis one-way analysis of variance by ranks** one of the following is true with regard to the rank-order data that are evaluated: a) The data are in a rank-order format, since it is the only format in which scores are available; or b) The data have been transformed into a rank-order format from an interval/ratio format, since the researcher has reason to believe that one or more of the assumptions of the **single-factor between-subjects analysis of variance (Test 21)** (which is the parametric analog of the **Kruskal–Wallis test**) are saliently violated. It should be noted that when a researcher elects to transform a set of interval/ratio data into ranks, information is sacrificed. This latter fact accounts for why there is reluctance among some researchers to employ nonparametric tests such as the **Kruskal–Wallis one-way analysis of variance by ranks**, even if there is reason to believe that one or more of the assumptions of the **single-factor between-subjects analysis of variance** have been violated.

Various sources (e.g., Conover (1980, 1999), Daniel (1990), and Marascuilo and McSweeney (1977)) note that the **Kruskal–Wallis one-way analysis of variance by ranks** is based on the following assumptions: a) Each sample has been randomly selected from the population it represents; b) The k samples are independent of one another; c) The dependent variable (which is subsequently ranked) is a continuous random variable. In truth, this assumption, which is common to many nonparametric tests, is often not adhered to, in that such tests are often employed with a dependent variable that represents a discrete random variable; and d) The underlying distributions from which the samples are derived are identical in shape. The shapes of the underlying population distributions, however, do not have to be normal. Maxwell and Delaney (1990) point out that the assumption of identically shaped distributions implies equal dispersion of data within each distribution. Because of this, they note that, like the **single-factor**

between-subjects analysis of variance, the **Kruskal–Wallis one-way analysis of variance by ranks** assumes homogeneity of variance with respect to the underlying population distributions. Because the latter assumption is not generally acknowledged for the **Kruskal–Wallis one-way analysis of variance by ranks**, it is not uncommon for sources to state that violation of the homogeneity of variance assumption justifies use of the **Kruskal–Wallis one-way analysis of variance by ranks** in lieu of the **single-factor between-subjects analysis of variance**. It should be pointed out, however, that there is some empirical research which suggests that the sampling distribution for the **Kruskal–Wallis test** statistic is not as affected by violation of the homogeneity of variance assumption as is the F distribution (which is the sampling distribution for the **single-factor between-subjects analysis of variance**). One reason cited by various sources for employing the **Kruskal–Wallis one-way analysis of variance by ranks**, is that by virtue of ranking interval/ratio data a researcher can reduce or eliminate the impact of **outliers**. As noted in Section VII of the **t test for two independent samples**, since **outliers** can dramatically influence variability, they can be responsible for heterogeneity of variance between two or more samples. In addition, **outliers** can have a dramatic impact on the value of a sample mean.

Zimmerman and Zumbo (1993) note that the result obtained with the **Kruskal–Wallis one-way analysis of variance by ranks** is equivalent (in terms of the derived probability value) to that which will be obtained if the rank-orders employed for the **Kruskal–Wallis test** are evaluated with a **single-factor between-subjects analysis of variance**.

II. Example

Example 22.1 is identical to Example 21.1 (which is evaluated with the **single-factor between-subjects analysis of variance**). In evaluating Example 22.1 it will be assumed that the ratio data (i.e., the number of nonsense syllables correctly recalled) are rank-ordered, since one or more of the assumptions of the **single-factor between-subjects analysis of variance** have been saliently violated.

Example 22.1 *A psychologist conducts a study to determine whether or not noise can inhibit learning. Each of 15 subjects is randomly assigned to one of three groups. Each subject is given 20 minutes to memorize a list of 10 nonsense syllables which she is told she will be tested on the following day. The five subjects assigned to **Group 1**, the **no noise** condition, study the list of nonsense syllables while they are in a quiet room. The five subjects assigned to **Group 2**, the **moderate noise** condition, study the list of nonsense syllables while listening to classical music. The five subjects assigned to **Group 3**, the **extreme noise** condition, study the list of nonsense syllables while listening to rock music. The number of nonsense syllables correctly recalled by the 15 subjects follows: **Group 1:** 8, 10, 9, 10, 9; **Group 2:** 7, 8, 5, 8, 5; **Group 3:** 4, 8, 7, 5, 7. Do the data indicate that noise influenced subjects' performance?*

III. Null versus Alternative Hypotheses

Null hypothesis $H_0: \theta_1 = \theta_2 = \theta_3$

(The median of the population Group 1 represents equals the median of the population Group 2 represents equals the median of the population Group 3 represents. With respect to the sample data, when there are an equal number of subjects in each group, the sums of the ranks will be equal for all k groups — i.e., $\sum R_1 = \sum R_2 = \sum R_3$. A more general way of stating this (which also encompasses designs involving unequal sample sizes) is that the means of the ranks of the k groups will be equal (i.e., $\bar{R}_1 = \bar{R}_2 = \bar{R}_3$).)

Alternative hypothesis

H_1 : Not H_0

(This indicates that there is a difference between at least two of the $k = 3$ population medians. It is important to note that the alternative hypothesis should not be written as follows: H_1 : $\theta_1 \neq \theta_2 \neq \theta_3$. The reason why the latter notation for the alternative hypothesis is incorrect is because it implies that all three population medians must differ from one another in order to reject the null hypothesis. With respect to the sample data, if there are an equal number of subjects in each group, when the alternative hypothesis is true the sums of the ranks of at least two of the k groups will not be equal. A more general way of stating this (which also encompasses designs involving unequal sample sizes) is that the means of the ranks of at least two of the k groups will not be equal. In this book it will be assumed (unless stated otherwise) that the alternative hypothesis for the **Kruskal–Wallis one-way analysis of variance by ranks** is stated **nondirectionally**.)¹

IV. Test Computations

The data for Example 22.1 are summarized in Table 22.1. The total number of subjects employed in the experiment is $N = 15$. There are $n_j = n_1 = n_2 = n_3 = 5$ subjects in each group. The original interval/ratio scores of the subjects are recorded in the columns labelled X_1 , X_2 , and X_3 . The adjacent columns R_1 , R_2 , and R_3 contain the rank-order assigned to each of the scores. The rankings for Example 22.1 are summarized in Table 22.2.

The ranking protocol employed for the **Kruskal–Wallis one-way analysis of variance by ranks** is the same as that employed for the **Mann–Whitney U test**. In Table 22.2 the two-digit subject identification number indicates the order in which a subject’s score appears in Table 22.1 followed by his/her group. Thus, Subject i, j is the i^{th} subject in Group j .

Table 22.1 Data for Example 22.1

Group 1		Group 2		Group 3	
X_1	R_1	X_2	R_2	X_3	R_3
8	9.5	7	6	4	1
10	14.5	8	9.5	8	9.5
9	12.5	5	3	7	6
10	14.5	8	9.5	5	3
9	12.5	5	3	7	6
$\Sigma R_1 = 63.5$		$\Sigma R_2 = 31$		$\Sigma R_3 = 25.5$	
$\bar{R}_1 = \frac{\Sigma R_1}{n_1} = \frac{63.5}{5} = 12.7$		$\bar{R}_2 = \frac{\Sigma R_2}{n_2} = \frac{31}{5} = 6.2$		$\bar{R}_3 = \frac{\Sigma R_3}{n_3} = \frac{25.5}{5} = 5.1$	

Table 22.2 Rankings for the Kruskal–Wallis Test for Example 22.1

Subject identification number	1,3	3,2	5,2	4,3	1,2	3,3	5,3	1,1	2,2	4,2	2,3	3,1	5,1	2,1	4,1
Number correct	4	5	5	5	7	7	7	8	8	8	8	9	9	10	10
Rank prior to tie adjustment	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Tie-adjusted rank	1	3	3	3	6	6	6	9.5	9.5	9.5	9.5	12.5	12.5	14.5	14.5

A brief summary of the ranking protocol employed in Table 22.2 follows:

a) All $N = 15$ scores are arranged in order of magnitude (irrespective of group membership), beginning on the left with the lowest score and moving to the right as scores increase. This is done in the second row of Table 22.2.

b) In the third row of Table 22.2, all $N = 15$ scores are assigned a rank. Moving from left to right, a rank of 1 is assigned to the score that is furthest to the left (which is the lowest score), a rank of 2 is assigned to the score that is second from the left (which, if there are no ties, will be the second lowest score), and so on until the score at the extreme right (which will be the highest score) is assigned a rank equal to N (if there are no ties for the highest score).

c) In instances where two or more subjects have the same score, the average of the ranks involved is assigned to all scores tied for a given rank. The tie-adjusted ranks are listed in the fourth row of Table 22.2. For a comprehensive discussion of how to handle tied ranks, the reader should review the description of the ranking protocol in Section IV of the **Mann–Whitney U test**.

It should be noted that, as is the case with the **Mann–Whitney U test**, it is permissible to reverse the ranking protocol described above. Specifically, one can assign a rank of 1 to the highest score, a rank of 2 to the second highest score, and so on, until reaching the lowest score which is assigned a rank equal to the value of N . This reverse ranking protocol will yield the same value for the **Kruskal–Wallis test** statistic as the protocol employed in Table 22.2.

Upon rank-ordering the scores of the $N = 15$ subjects, the sum of the ranks is computed for each group. In Table 22.1 the sum of the ranks of the j^{th} group is represented by the notation ΣR_j . Thus, $\Sigma R_1 = 63.5$, $\Sigma R_2 = 31$, $\Sigma R_3 = 25.5$.

The chi-square distribution is used to approximate the **Kruskal–Wallis test** statistic. Equation 22.1 is employed to compute the chi-square approximation of the **Kruskal–Wallis test** statistic (which is represented in most sources by the notation H).

$$H = \frac{12}{N(N + 1)} \sum_{j=1}^k \left[\frac{(\Sigma R_j)^2}{n_j} \right] - 3(N + 1) \quad (\text{Equation 22.1})$$

Note that in Equation 22.1, the term $\sum_{j=1}^k [(\Sigma R_j)^2 / n_j]$ indicates that for each of the k groups, the sum of the ranks is squared and then divided by the number of subjects in the group. Upon doing this for all k groups, the resulting values are summed. Substituting the appropriate values from Example 22.1 in Equation 22.1, the value $H = 8.44$ is computed.

$$H = \frac{12}{(15)(15 + 1)} \left[\frac{(63.5)^2}{5} + \frac{(31)^2}{5} + \frac{(25.5)^2}{5} \right] - (3)(15 + 1) = 8.44$$

V. Interpretation of the Test Results

In order to reject the null hypothesis, the computed value $H = \chi^2$ must be equal to or greater than the tabled critical chi-square value at the prespecified level of significance. The computed chi-square value is evaluated with Table A4 (**Table of the Chi-Square Distribution**) in the **Appendix**. For the appropriate degrees of freedom, the tabled $\chi^2_{.95}$ value (which is the chi-square value at the 95th percentile) and the tabled $\chi^2_{.99}$ value (which is the chi-square value at the 99th percentile) are employed as the .05 and .01 critical values for evaluating a nondirectional alternative hypothesis. The number of degrees of freedom employed in the analysis are computed with Equation 22.2. Thus, $df = 3 - 1 = 2$.

$$df = k - 1$$

Equation 22.2)

For $df = 2$, the tabled critical .05 and .01 chi-square values are $\chi^2_{.05} = 5.99$ and $\chi^2_{.01} = 9.21$. Since the computed value $H = 8.44$ is greater than $\chi^2_{.05} = 5.99$, the alternative hypothesis is supported at the .05 level. Since, however, $H = 8.44$ is less than $\chi^2_{.01} = 9.21$, the alternative hypothesis is not supported at the .01 level.² A summary of the analysis of Example 22.1 with the **Kruskal–Wallis one-way analysis of variance by ranks** follows: It can be concluded that there is a significant difference between at least two of the three groups exposed to different levels of noise. This result can be summarized as follows: $H(2) = 8.44$, $p < .05$.

It should be noted that when the data for Example 22.1 are evaluated with a **single-factor between-subjects analysis of variance**, the null hypothesis can be rejected at both the .05 and .01 levels (although it barely achieves significance at the latter level and, in the case of the **Kruskal–Wallis test**, the result just falls short of significance at the .01 level). The slight discrepancy between the results of the two tests reflects the fact that, as a general rule (assuming that none of the assumptions of the analysis of variance are saliently violated), the **Kruskal–Wallis one-way analysis of variance by ranks** provides a less powerful test of an alternative hypothesis than the **single-factor between-subjects analysis of variance**.

VI. Additional Analytical Procedures for the Kruskal–Wallis One-Way Analysis of Variance by Ranks and/or Related Tests

1. Tie correction for the Kruskal–Wallis one-way analysis of variance by ranks Some sources recommend that if there is an excessive number of ties in the overall distribution of N scores, the value of the **Kruskal–Wallis test** statistic be adjusted. The tie correction results in a small increase in the value of H (thus providing a slightly more powerful test of the alternative hypothesis). Equation 22.3 is employed to compute the value C , which represents the tie correction factor for the **Kruskal–Wallis one-way analysis of variance by ranks**.

$$C = 1 - \frac{\sum_{i=1}^s (t_i^3 - t_i)}{N^3 - N} \quad \text{(Equation 22.3)}$$

Where: s = The number of sets of ties

t_i = The number of tied scores in the i^{th} set of ties

The notation $\sum_{i=1}^s (t_i^3 - t_i)$ indicates the following: a) For each set of ties, the number of ties in the set is subtracted from the cube of the number of ties in that set; and b) The sum of all the values computed in part a) is obtained. The correction for ties will now be computed for Example 22.1. In the latter example there are $s = 5$ sets of ties (i.e., three scores of 5, three scores of 7, four scores of 8, two scores of 9, and two scores of 10). Thus:

$$\sum_{i=1}^s (t_i^3 - t_i) = [(3)^3 - 3] + [(3)^3 - 3] + [(4)^3 - 4] + [(2)^3 - 2] + [(2)^3 - 2] = 120$$

Employing Equation 22.3, the value $C = .964$ is computed.

$$C = 1 - \frac{120}{(15)^3 - 15} = .964$$

H_C , which represents the tie-corrected value of the **Kruskal–Wallis test** statistic, is computed with Equation 22.4.

$$H_C = \frac{H}{C} \quad (\text{Equation 22.4})$$

Employing Equation 22.4, the tie-corrected value $H_C = 8.76$ is computed.

$$H_C = \frac{8.44}{.964} = 8.76$$

As is the case with $H = 8.44$ computed with Equation 22.1, the value $H_C = 8.76$ computed with Equation 22.4 is significant at the .05 level (since it is greater than $\chi^2_{.05} = 5.99$), but is not significant at the .01 level (since it is less than $\chi^2_{.01} = 9.21$). Although Equation 22.4 results in a slightly less conservative test than Equation 22.1, in this instance the two equations lead to identical conclusions with respect to the null hypothesis.

2. Pairwise comparisons following computation of the test statistic for the Kruskal–Wallis one-way analysis of variance by ranks Prior to reading this section the reader should review the discussion of comparisons in Section VI of the **single-factor between-subjects analysis of variance**. As is the case with the omnibus F value computed for the **single-factor between-subjects analysis of variance**, the H value computed with Equation 22.1 is based on an evaluation of all k groups. When the value of H is significant, it does not indicate whether just two or, in fact, more than two groups differ significantly from one another. In order to answer the latter question, it is necessary to conduct comparisons contrasting specific groups with one another. This section will describe methodologies that can be employed for conducting **simple/pairwise comparisons** following the computation of an H value.³

In conducting a simple comparison, the null hypothesis and nondirectional alternative hypothesis are as follows: $H_0: \theta_a = \theta_b$ versus $H_1: \theta_a \neq \theta_b$. In the aforementioned hypotheses, θ_a and θ_b represent the medians of the populations represented by the two groups involved in the comparison. The alternative hypothesis can also be stated directionally as follows: $H_1: \theta_a > \theta_b$ or $H_1: \theta_a < \theta_b$.

Various sources (e.g., Daniel (1990) and Siegel and Castellan (1988)) describe a comparison procedure for the **Kruskal–Wallis one-way analysis of variance by ranks** (described by Dunn (1964)), which is essentially the application of the **Bonferroni–Dunn method** described in Section VI of the **single-factor between-subjects analysis of variance** to the **Kruskal–Wallis test** model. Through use of Equation 22.5, the procedure allows a researcher to identify the minimum required difference between the means of the ranks of any two groups (designated as CD_{KW}) in order for them to differ from one another at the prespecified level of significance.⁴

$$CD_{KW} = z_{adj} \sqrt{\frac{N(N+1)}{12} \left(\frac{1}{n_a} + \frac{1}{n_b} \right)} \quad (\text{Equation 22.5})$$

Where: n_a and n_b represent the number of subjects in each of the groups involved in the simple comparison

The value of z_{adj} is obtained from **Table A1 (Table of the Normal Distribution)** in the **Appendix**. In the case of a nondirectional alternative hypothesis, z_{adj} is the z value above which

a proportion of cases corresponding to the value $\alpha_{FW}/2c$ falls (where c is the total number of comparisons that are conducted). In the case of a directional alternative hypothesis, z_{adj} is the z value above which a proportion of cases corresponding to the value α_{FW}/c falls. When all possible pairwise comparisons are made $c = [k(k - 1)]/2$, and thus, $2c = k(k - 1)$. In Example 22.1 the number of pairwise/simple comparisons that can be conducted are $c = [3(3 - 1)]/2 = 3$ — specifically, Group 1 versus Group 2, Group 1 versus Group 3, and Group 2 versus Group 3.

The value of z_{adj} will be a function of both the maximum **familywise Type I error rate** (α_{FW}) the researcher is willing to tolerate and the total number of comparisons that are conducted. When a limited number of comparisons are planned prior to collecting the data, most sources take the position that a researcher is not obliged to control the value of α_{FW} . In such a case, the **per comparison Type I error rate** (α_{PC}) will be equal to the prespecified value of alpha. When α_{FW} is not adjusted, the value of z_{adj} employed in Equation 22.5 will be the tabled critical z value that corresponds to the prespecified level of significance. Thus, if a nondirectional alternative hypothesis is employed and $\alpha = \alpha_{PC} = .05$, the tabled critical two-tailed .05 value $z_{.05} = 1.96$ is used to represent z_{adj} in Equation 22.5. If $\alpha = \alpha_{PC} = .01$, the tabled critical two-tailed .01 value $z_{.01} = 2.58$ is used in Equation 22.5. In the same respect, if a directional alternative hypothesis is employed, the tabled critical .05 and .01 one-tailed values $z_{.05} = 1.65$ and $z_{.01} = 2.33$ are used for z_{adj} in Equation 22.5.

When comparisons are not planned beforehand, it is generally acknowledged that the value of α_{FW} must be controlled so as not to become excessive. The general approach for controlling the latter value is to establish a **per comparison Type I error rate** which insures that α_{FW} will not exceed some maximum value stipulated by the researcher. One method for doing this (described under the **single-factor between-subjects analysis of variance** as the **Bonferroni-Dunn method**) establishes the **per comparison Type I error rate** by dividing the maximum value one will tolerate for the **familywise Type I error rate** by the total number of comparisons conducted. Thus, in Example 22.1, if one intends to conduct all three pairwise comparisons and wants to insure that α_{FW} does not exceed .05, $\alpha_{PC} = \alpha_{FW}/c = .05/3 = .0167$. The latter proportion is used to determine the value of z_{adj} . As noted earlier, if a directional alternative hypothesis is employed for a comparison, the value of z_{adj} employed in Equation 22.5 is the z value above which a proportion equal to $\alpha_{PC} = \alpha_{FW}/c$ of the cases falls. In [Table A1](#), the z value that corresponds to the proportion .0167 is $z = 2.13$. By employing $z_{adj} = 2.13$ in Equation 22.5, one can be assured that within the “family” of three pairwise comparisons, α_{FW} will not exceed .05 (assuming all of the comparisons are directional). If a nondirectional alternative hypothesis is employed for all of the comparisons, the value of z_{adj} will be the z value above which a proportion equal to $\alpha_{FW}/2c = \alpha_{PC}/2$ of the cases falls. Since $\alpha_{PC}/2 = .0167/2 = .0083$, $z = 2.39$. By employing $z_{adj} = 2.39$ in Equation 22.5, one can be assured that α_{FW} will not exceed .05.⁵

Table 22.3 Difference Scores Between Pairs of Mean Ranks for Example 22.1

$ \bar{R}_1 - \bar{R}_2 = 12.7 - 6.2 = 6.5$
$ \bar{R}_1 - \bar{R}_3 = 12.7 - 5.1 = 7.6$
$ \bar{R}_2 - \bar{R}_3 = 6.2 - 5.1 = 1.1$

In order to employ the CD_{KW} value computed with Equation 22.5, it is necessary to determine the mean rank for each of the k groups, and then compute the absolute value of the difference between the mean ranks of each pair of groups that are compared.⁶ In [Table 22.1](#) the

following values for the mean ranks of the groups are computed: $\bar{R}_1 = 12.7$, $\bar{R}_2 = 6.2$, $\bar{R}_3 = 5.1$. Employing the latter values, Table 22.3 summarizes the difference scores between pairs of mean ranks.

If any of the differences between mean ranks is equal to or greater than the CD_{KW} value computed with Equation 22.5, a comparison is declared significant. Equation 22.5 will now be employed to evaluate the nondirectional alternative hypothesis $H_1: \theta_a \neq \theta_b$ for all three pairwise comparisons. Since it will be assumed that the comparisons are unplanned and that the researcher does not want the value of α_{FW} to exceed .05, the value $z_{adj} = 2.39$ will be used in computing CD_{KW} .

$$CD_{KW} = (2.39) \sqrt{\frac{(15)(15 + 1)}{12} \left(\frac{1}{5} + \frac{1}{5} \right)} = (2.39)(2.83) = 6.76$$

The obtained value $CD_{KW} = 6.76$ indicates that any difference between the mean ranks of two groups that is equal to or greater than 6.76 is significant. With respect to the three pairwise comparisons, the only difference between mean ranks which is greater than $CD_{KW} = 6.76$ is $|\bar{R}_1 - \bar{R}_3| = 7.6$. Thus, we can conclude there is a significant difference between the performance of Group 1 and Group 3. Note that although $|\bar{R}_1 - \bar{R}_2| = 6.5$ is close to $CD_{KW} = 6.76$, it is not statistically significant unless the researcher is willing to tolerate a **familywise error rate** slightly above .05.⁷

An alternative strategy that can be employed for conducting pairwise comparisons for the **Kruskal–Wallis test model** is to use the **Mann–Whitney U test** for each comparison. Use of the latter test requires that the data for each pair of groups to be compared be rank-ordered, and that a separate U value be computed for that comparison. The exact distribution of the **Mann–Whitney test** statistic can only be used when the value of α_{PC} is equal to one of the probabilities documented in Table A11 (Table of Critical Values for the Mann–Whitney U Statistic) in the Appendix. When α_{PC} is a value other than those listed in Table A11, the normal approximation of the **Mann–Whitney U test** statistic must be employed.

When the **Mann–Whitney U test** is employed for the three pairwise comparisons, the following U values are computed: a) Group 1 versus Group 2: $U = 1$; b) Group 1 versus Group 3: $U = .5$; and c) Group 2 versus Group 3: $U = 10$. When the aforementioned U values are substituted in Equations 12.4 and 12.5 (the uncorrected and continuity-corrected normal approximations for the **Mann–Whitney U test**), the following absolute z values are computed: a) Group 1 versus Group 2: $z = 2.40$ and $z = 2.30$; b) Group 1 versus Group 3: $z = 2.51$ and $z = 2.40$; and c) Group 2 versus Group 3: $z = .52$ and $z = .42$. If we want to evaluate a nondirectional alternative hypothesis and insure that α_{FW} does not exceed .05, the value of α_{PC} is set equal to .0167. Table A11 cannot be employed, since it does not list two-tailed critical U values for $\alpha_{.0167}$. In order to evaluate the result of the normal approximation, we identify the tabled critical two-tailed .0167 z value in Table A1. In employing Equation 22.5 earlier in this section, we determined that the latter value is $z_{.0167} = 2.39$. Since the uncorrected values $z = 2.40$ (for the comparison Group 1 versus Group 2) and $z = 2.51$ (for the comparison Group 1 versus Group 3) computed with Equation 9.4 are greater than $z_{.0167} = 2.39$, the latter two comparisons are significant if we wish to insure that α_{FW} does not exceed .05. If the correction for continuity is employed, only the value $z = 2.40$ (for the comparison Group 1 versus Group 3), computed with Equation 12.5 is significant, since it exceeds $z_{.0167} = 2.39$. The Group 1 versus Group 2 comparison falls short of significance, since $z = 2.30$ is less than $z_{.0167} = 2.39$. Recollect that when Equation 22.5 is employed to conduct the same set of comparisons, the Group 1 versus Group 3 comparison is significant, whereas the Group 1 versus Group 2 comparison falls just

short of significance. Thus, the result obtained with Equation 22.5 is identical to that obtained when the continuity-corrected normal approximation of the **Mann–Whitney U test** is employed.

In the event the researcher elects not to control the value of α_{FW} and employs $\alpha_{PC} = .05$ in evaluating the three pairwise comparisons (once again assuming a nondirectional analysis), both the Group 1 versus Group 2 and Group 1 versus Group 3 comparisons are significant at the .05 level, regardless of which comparison procedure is employed. Specifically, both the uncorrected and corrected normal approximations are significant, since $z = 2.40$ and $z = 2.30$ (computed for the comparison Group 1 versus Group 2) and $z = 2.51$ and $z = 2.40$ (computed for the comparison Group 1 versus Group 3) are greater than the tabled critical two-tailed value $z_{.05} = 1.96$. Employing **Table A11**, we also determine that both the Group 1 versus Group 2 and Group 1 versus Group 3 comparisons are significant at the .05 level, since the computed values $U = 1$ and $U = .5$ are less than the tabled critical two-tailed .05 value $U_{.05} = 2$ (based on $n_1 = 5$ and $n_2 = 5$). If Equation 22.5 is employed for the same set of comparisons, $CD_{KW} = (1.96)(2.83) = 5.55$.⁸ Thus, if the latter equation is employed, the Group 1 versus Group 2 and Group 1 versus Group 3 comparisons are significant, since in both instances the difference between the mean ranks is greater than $CD_{KW} = 5.55$.

The above discussion of comparisons illustrates that, generally speaking, the results obtained with Equation 22.5 and the **Mann–Whitney U test** (as well as other comparison procedures that have been developed for the **Kruskal–Wallis one-way analysis of variance**) will be reasonably consistent with one another. As noted in Endnote 7 (as well as in the discussion of comparisons in Section VI of the **single-factor between-subjects analysis of variance**), in instances where two or more comparison procedures yield inconsistent results, the most effective way to clarify the status of the null hypothesis is to replicate a study one or more times. In the final analysis, the decision regarding which of the available comparison procedures to employ is usually not the most important issue facing the researcher conducting comparisons. The main issue is what maximum value one is willing to tolerate for α_{FW} . Additional sources on comparison procedures for the **Kruskal–Wallis test** model are Marascuilo and McSweeney (1977) (who describe a methodology for conducting complex comparisons), Wike (1978) (who provides a comparative analysis of a number of different procedures), and Hollander and Wolfe (1999).

The same logic employed for computing a confidence interval for a comparison described in Section VI of the **single-factor between-subjects analysis of variance** can be employed to compute a confidence interval for the **Kruskal–Wallis test** model. Specifically: Add to and subtract the computed value of CD_{KW} from the obtained difference between the two mean ranks involved in a comparison. Thus, $CI_{.95}$ (based on $\alpha_{FW} = .05$) for the comparison Group 1 versus Group 3 is computed as follows: $CI_{.95} = 7.6 \pm 6.76$. In other words, the researcher can be 95% confident (or the probability is .95) that the mean of the ranks in the population represented by Group 1 is between .84 and 14.36 units larger than the mean of the ranks in the population represented by Group 3. Marascuilo and McSweeney (1977) provide a more detailed discussion of the computation of a confidence interval for the **Kruskal–Wallis test** model.

VII. Additional Discussion of the Kruskal–Wallis One-Way Analysis of Variance by Ranks

1. Exact tables of the Kruskal–Wallis distribution Although an exact probability value can be computed for obtaining a configuration of ranks that is equivalent to or more extreme than the configuration observed in the data evaluated with the **Kruskal–Wallis one-way analysis of variance by ranks**, the chi-square distribution is generally employed to estimate the latter probability. As the values of k and N increase, the chi-square distribution provides a more accurate estimate of the exact Kruskal–Wallis distribution. Although most sources employ the chi-square

approximation regardless of the values of k and N , some sources recommend that exact tables be employed under certain conditions. Beyer (1968), Daniel (1990), and Siegel and Castellan (1988) provide exact Kruskal–Wallis probabilities for whenever $k = 3$ and the number of subjects in any of the samples is five or less. Use of the chi-square distribution for small sample sizes will generally result in a slight decrease in the power of the test (i.e., there is a higher likelihood of retaining a false null hypothesis). Thus, for small sample sizes, the tabled critical chi-square value should, in actuality, be a little lower than the value listed in [Table A4](#).

In point of fact, the exact tabled critical H values for $k = 3$ and $n_j = 5$ are $H_{.05} = 5.78$ and $H_{.01} = 7.98$. If the latter critical values are employed, the value $H = 8.44$ computed for Example 22.1 is significant at both the .05 and .01 levels, since $H = 8.44$ is greater than both $H_{.05} = 5.78$ and $H_{.01} = 7.98$. Thus, in this instance the exact tables and the chi-square approximation do not yield identical results.

2. Equivalency of the Kruskal–Wallis one-way analysis of variance by ranks and the Mann–Whitney U test when $k = 2$ In Section I it is noted that when $k = 2$ the **Kruskal–Wallis one-way analysis of variance by ranks** will yield a result that is equivalent to that obtained with the **Mann–Whitney U test**. To be more specific, the **Kruskal–Wallis test** will yield a result that is equivalent to the normal approximation for the **Mann–Whitney U test** when the correction for continuity is not employed (i.e., the result obtained with Equation 12.4). In order to demonstrate the equivalency of the two tests, Equation 22.1 is employed below to analyze the data for Example 12.1, which was previously evaluated with the **Mann–Whitney U test**.

$$H = \frac{12}{(10)(10 + 1)} \left[\frac{(19)^2}{5} + \frac{(36)^2}{5} \right] - (3)(10 + 1) = 3.15$$

Employing Equation 22.2, $df = 2 - 1 = 1$. For $df = 1$, the tabled critical .05 and .01 chi-square values are $\chi_{.05}^2 = 3.84$ and $\chi_{.01}^2 = 6.63$. Since the obtained value $H = 3.15$ is less than $\chi_{.05}^2 = 3.84$, the null hypothesis cannot be rejected.

Equation 12.4 yields the value $z = -1.78$ for the same set of data. When the latter value is squared, it yields a value that is equal to the H (chi-square) value computed with Equation 22.1 (i.e., $(z = -1.78)^2 = (\chi^2 = 3.15)$).⁹ It is also the case that the square of the tabled critical z value employed for the normal approximation of the **Mann–Whitney U test** will always be equal to the tabled critical chi-square value employed for the **Kruskal–Wallis test** at the same level of significance. Thus, the square of the tabled critical two-tailed value $z_{.05} = 1.96$ employed for the normal approximation of the **Mann–Whitney U test** equals $\chi_{.05}^2 = 3.84$ employed for the **Kruskal–Wallis test** (i.e., $(z = 1.96)^2 = (\chi^2 = 3.84)$).

3. Power-efficiency of the Kruskal–Wallis one-way analysis of variance by ranks When the underlying population distributions are normal, the **asymptotic relative efficiency** (which is discussed in Section VII of the **Wilcoxon signed-ranks test (Test 6)**) of the **Kruskal–Wallis one-way analysis of variance by ranks** is .955 (when contrasted with the **single-factor between-subjects analysis of variance**). For population distributions that are not normal, the asymptotic relative efficiency of the **Kruskal–Wallis test** is generally equal to or greater than 1. As a general rule, proponents of nonparametric tests take the position that when a researcher has reason to believe that the normality assumption of the **single-factor between-subjects analysis of variance** has been saliently violated, the **Kruskal–Wallis one-way analysis of variance by ranks** provides a powerful test of the comparable alternative hypothesis.

4. Alternative nonparametric rank-order procedures for evaluating a design involving k independent samples In addition to the **Kruskal–Wallis one-way analysis of variance by ranks**, a number of other nonparametric procedures for two or more independent samples have been developed that can be employed with ordinal data. Among the more commonly cited alternative procedures are the following: a) **The van der Waerden normal-scores test for k independent samples (Test 23)** (Van der Waerden (1953/1953)), which is described in the next chapter, as well as alternative **normal-scores tests** developed by Terry and Hoeffding (Terry (1952)) and Bell and Doksum (1965); b) **The Jonckheere–Terpstra test for ordered alternatives** (Jonckheere (1954); Terpstra (1952)) can be employed when the alternative hypothesis for a k independent samples design specifies the rank-order of the k population medians. The latter test is described in Daniel (1990) and Hollander and Wolfe (1999); c) **The median test for independent samples (Test 16e)** (discussed in Section VI of the **chi-square test for $r \times c$ tables (Test 16)**) can be extended to three or more independent samples by dichotomizing k samples with respect to their median values; and d) **The Kolmogorov–Smirnov test for two independent samples (Test 13)** (Kolmogorov (1933) and Smirnov (1939)) can be extended to three or more independent samples. The use of the latter test with more than two samples is discussed in Bradley (1968) and Conover (1980, 1999). Sheskin (1984) describes some of the aforementioned tests in greater detail, as well as citing additional procedures that can be employed for k independent samples designs involving rank-order data.

VIII. Additional Examples Illustrating the Use of the Kruskal–Wallis One-Way Analysis of Variance by Ranks

The **Kruskal–Wallis one-way analysis of variance by ranks** can be employed to evaluate any of the additional examples noted for the **single-factor between-subjects analysis of variance**, if the data for the latter examples are rank-ordered. In addition, the **Kruskal–Wallis test** can be used to evaluate the data for any of the additional examples noted for the **t test for two independent samples (Test 11)** and the **Mann–Whitney U test**. Examples 22.2 and 22.3 are two additional examples that can be evaluated with the **Kruskal–Wallis one-way analysis of variance by ranks**. Example 22.2 is an extension of Example 12.2 (evaluated with the **Mann–Whitney U test**) to a design involving $k = 3$ groups. In Example 22.2 (as well as Example 22.3) the original data are presented as ranks, rather than in an interval/ratio format.¹⁰ Since the rank-orderings for Example 22.2 are identical to those employed in Example 22.1, it yields the same result. Example 22.3 (which is also an extension of Example 12.2) illustrates the use of the **Kruskal–Wallis one-way analysis of variance by ranks** with a design involving $k = 4$ groups and unequal sample sizes.

Example 22.2 *Doctor Radical, a math instructor at Logarithm University, has three classes in advanced calculus. There are five students in each class. The instructor uses a programmed textbook in Class 1, a conventional textbook in Class 2, and his own printed notes in Class 3. At the end of the semester, in order to determine if the type of instruction employed influences student performance, Dr. Radical has another math instructor, Dr. Root, rank the 15 students in the three classes with respect to math ability. The rankings of the students in the three classes follow: **Class 1:** 9.5, 14.5, 12.5, 14.5, 12.5; **Class 2:** 6, 9.5, 3, 9.5, 3; and **Class 3:** 1, 9.5, 6, 3, 6 (assume the lower the rank, the better the student).*

Note that whereas in Example 22.1, Group 1 (the group with the highest sum of ranks) has the best performance, in Example 22.2, Class 3 (the class with the lowest sum of ranks) is evaluated as the best class. This is the case, since in Example 22.2 the lower a student's rank the

better the student, whereas in Example 22.1 the lower a subject's rank, the poorer the subject performed.

Example 22.3 *Doctor Radical, a math instructor at Logarithm University, has four classes in advanced calculus. There are six students in Class 1, seven students in Class 2, eight students in Class 3, and six students in Class 4. The instructor uses a programmed textbook in Class 1, a conventional textbook in Class 2, his own printed notes in Class 3, and no written instructional material in Class 4. At the end of the semester, in order to determine if the type of instruction employed influences student performance, Dr. Radical has another math instructor, Dr. Root, rank the 27 students in the four classes with respect to math ability. The rankings of the students in the four classes follow: **Class 1:** 1, 2, 4, 6, 8, 9; **Class 2:** 10, 14, 18, 20, 21, 25, 26; **Class 3:** 3, 5, 7, 11, 12, 16, 17, 22; **Class 4:** 13, 15, 19, 23, 24, 27 (assume the lower the rank, the better the student).*

Example 22.3 provides us with the following information: $n_1 = 6$, $n_2 = 7$, $n_3 = 8$, $n_4 = 6$, and $N = 27$. The sums of the ranks for the four groups are: $\sum R_1 = 30$, $\sum R_2 = 134$, $\sum R_3 = 93$, $\sum R_4 = 121$. Substituting the appropriate values in Equation 22.1, the value $H = 14.99$ is computed.

$$H = \frac{12}{(27)(27 + 1)} \left[\frac{(30)^2}{6} + \frac{(134)^2}{7} + \frac{(93)^2}{8} + \frac{(121)^2}{6} \right] - (3)(27 + 1) = 14.99$$

Employing Equation 22.2, $df = 4 - 1 = 3$. For $df = 3$, the tabled critical .05 and .01 chi-square values are $\chi_{.05}^2 = 7.81$ and $\chi_{.01}^2 = 11.34$. Since the obtained value $H = 14.99$ is greater than both of the aforementioned critical values, the null hypothesis can be rejected at both the .05 and .01 levels. Thus, one can conclude that the rankings for at least two of the four classes differed significantly from one another. Although multiple comparisons will not be conducted for this example, visual inspection of the data suggests that the rankings for Class 1 are dramatically superior to those for the other three classes.

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Endnotes

1. Although it is possible to conduct a directional analysis, such an analysis will not be described with respect to the **Kruskal–Wallis one-way analysis of variance by ranks**. A discussion of a directional analysis when $k = 2$ can be found under the **Mann–Whitney U test**. A discussion of the evaluation of a directional alternative hypothesis when $k \geq 3$ can be found in Section VII of the **chi-square goodness-of-fit test (Test 8)**. Although the latter discussion is in reference to analysis of a k independent samples design involving categorical data, the general principles regarding analysis of a directional alternative hypothesis when $k \geq 3$ are applicable to the **Kruskal–Wallis one-way analysis of variance by ranks**.
2. As noted in Section IV, the chi-square distribution provides an approximation of the **Kruskal–Wallis test** statistic. Although the chi-square distribution provides an excellent approximation of the Kruskal–Wallis sampling distribution, some sources recommend the use of exact probabilities for small sample sizes. Exact tables of the Kruskal–Wallis distribution are discussed in Section VII.

3. In the discussion of comparisons under the **single-factor between-subjects analysis of variance**, it is noted that a **simple** (also known as a **pairwise**) **comparison** is a comparison between any two groups in a set of k groups.
4. Note that in Equation 22.5, as the value of N increases, the value computed for CD_{KW} will also increase because of the greater number (range of values) of rank-orderings required for the data.
5. The rationale for the use of the proportions .0167 and .0083 in determining the appropriate value for z_{adj} is as follows. In the case of a one-tailed/directional analysis, the relevant probability/proportion employed is based on only one of the two tails of the normal distribution. Consequently, the proportion of the normal curve that is used to determine the value of z_{adj} will be a proportion that is equal to the value of α_{PC} in the appropriate tail of the distribution (which is designated in the alternative hypothesis). The value $z = 2.13$ is employed, since the proportion of cases that falls above $z = 2.13$ in the right tail of the distribution is .0167, and the proportion of cases that falls below $z = -2.13$ in the left tail of the distribution is .0167. In the case of a two-tailed/nondirectional analysis, the relevant probability/proportion employed is based on both tails of the distribution. Consequently, the proportion of the normal curve that is used to determine the value of z_{adj} will be a proportion that is equal to the value of $\alpha_{PC}/2$ in each tail of the distribution. The proportion $\alpha_{PC}/2 = .0167/2 = .0083$ is employed for a two-tailed/nondirectional analysis, since one-half of the proportion that comprises $\alpha_{PC} = .0167$ comes from the left tail of the distribution and the other half from the right tail. Consequently, the value $z = 2.39$ is employed, since the proportion of cases that falls above $z = 2.39$ in the right tail of the distribution is .0083, and the proportion of cases that falls below $z = -2.39$ in the left tail of the distribution is .0083.
6. It should be noted that when a directional alternative hypothesis is employed, the sign of the difference between the two mean ranks must be consistent with the prediction stated in the directional alternative hypothesis. When a nondirectional alternative hypothesis is employed, the direction of the difference between two mean ranks is irrelevant.
7. a) Many researchers would probably be willing to tolerate a somewhat higher familywise Type I error rate than .05. In such a case the difference $|R_1 - R_2| = 6.5$ will be significant, since the value of z_{adj} employed in Equation 22.5 will be less than $z = 2.39$, thus resulting in a lower value for CD_{KW} .
 b) When there are a large number of ties in the data, a modified version of Equation 22.5 is recommended by some sources (e.g., Daniel (1990)), which reduces the value of CD_{KW} by a minimal amount. Marascuilo and McSweeney (1977, p. 318) recommend that when ties are present in the data, the tie correction factor $C = .964$ computed with Equation 22.3 be multiplied by the term in the radical of Equation 22.5. When the latter is done with the data for Example 22.1 (as noted below), the value $CD_{KW} = 6.64$ is obtained. As is the case with Equation 22.5, only the Group 1 versus Group 3 pairwise difference is significant.

$$CD_{KW} = (2.39) \sqrt{(.964) \left(\frac{(15)(15 + 1)}{12} \right) \left(\frac{1}{5} + \frac{1}{5} \right)} = (2.39)(2.77) = 6.64$$

- c) In contrast to Equation 22.5, Conover (1980, 1999) employs Equation 22.6 for conducting pairwise comparisons. Conover (1980, 1999) states that Equation 22.6 is

recommended when there are no ties. Although he provides a tie correction equation, he notes that the result obtained with the tie correction equation will be very close to that obtained with Equation 22.6 when there are only a few ties in the data. Because of the latter, Equation 22.6 will be employed in the discussion to follow. The latter equation can yield a substantially lower CD_{KW} value than Equation 22.5. Equation 22.6 is analogous to Equation 23.4, which Conover (1980, 1999) recommends for conducting comparisons for the **van der Waerden normal-scores test for k independent samples** (which is discussed in the next chapter). Note that if the element $[(N - 1 - H)/(N - k)]$ is omitted from the radical in Equation 22.6, it becomes Equation 22.5. It is demonstrated below that when Equation 22.6 is employed with the data for Example 22.1, the value $CD_{KW} = 4.60$ is obtained. If the latter CD_{KW} value is used, both the Group 1 versus Group 3 and Group 1 versus Group 2 comparisons are significant (the latter being the case, since the obtained difference of 6.5 for the Group 1 versus Group 2 comparison is greater than $CD_{KW} = 4.60$).

$$\begin{aligned}
 CD_{KW} &= z_{adj} \sqrt{\left(\frac{N(N+1)}{12} \right) \left(\frac{N-1-H}{N-k} \right) \left(\frac{1}{n_a} + \frac{1}{n_b} \right)} && \text{(Equation 22.6)} \\
 &= (2.39) \sqrt{\left(\frac{15(15+1)}{12} \right) \left(\frac{15-1-8.44}{15-3} \right) \left(\frac{1}{5} + \frac{1}{5} \right)} = 4.60
 \end{aligned}$$

Although Equation 22.6 allows for a more powerful test of an alternative hypothesis than Equation 22.5, some sources would argue that it does not adequately control the familywise Type I error rate. Hollander and Wolfe (1999) discuss alternative approaches for conducting pairwise comparisons for the **Kruskal–Wallis test**.

In view of the fact that sources do not agree on the methodology for conducting pairwise comparisons, if two or more methods yield dramatically different results for a specific comparison, one or more replication studies employing reasonably large sample sizes should clarify whether or not an obtained difference is reliable, as well as the magnitude of the difference (if, in fact, one exists).

8. In Equation 22.5 the value $z_{.05} = 1.96$ is employed for z_{adj} , and the latter value is multiplied by 2.83, which is the value computed for the term in the radical of the equation for Example 22.1.
9. The slight discrepancy is due to rounding off error, since the actual absolute value of z computed with Equation 12.4 is 1.7756.
10. In accordance with one of the assumptions noted in Section I for the **Kruskal–Wallis one-way analysis of variance by ranks**, in both Examples 22.2 and 22.3 it is assumed that Dr. Radical implicitly or explicitly evaluates the N students on a continuous interval/ratio scale prior to converting the data into a rank-order format.

Test 23

The van der Waerden Normal-Scores Test for k Independent Samples (Nonparametric Test Employed with Ordinal Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test Are k independent samples derived from identical population distributions?

Relevant background information on test The **van der Waerden normal-scores test for k independent samples** (van der Waerden (1952/1953) is employed with ordinal (rank-order) data in a hypothesis testing situation involving a design with two or more independent samples. The **van der Waerden test** is one of a number of normal-scores tests that have been developed for evaluating data. **Normal-scores tests** transform a set of rank-orders into a set of standard deviation scores (i.e., z scores) based on the standard normal distribution. Marascuilo and McSweeney (1977, p. 280) note that normal-scores tests are often described as **distribution free tests**, insofar as the shape of the underlying population distribution(s) for the original data has little effect on the results of such tests. Because of their minimal assumptions, normal-scores tests are categorized as nonparametric tests.

Just as converting a set of interval/ratio data into rank-orders transforms the data into what is essentially a uniform distribution, transforming a set of ranks into normal-scores transforms the ranks into essentially a normal distribution. Although the normal-scores transformation results in some loss of the information contained in the original data, much of the information is retained, albeit in a different format. Conover (1980, 1999) notes that when the underlying population distributions for the original data are normal, by virtue of employing a normal-scores transformation, the statistical power of the resulting normal-scores test will generally be equal to that of the analogous parametric test, and that when the underlying population distributions for the original data are not normal, the power of the normal-scores test may actually be higher than that of the analogous parametric test.¹

If the result of the **van der Waerden normal-scores test for k independent samples** is significant, it indicates there is a significant difference between at least two of the samples in the set of k samples. Consequently, the researcher can conclude there is a high likelihood that at least two of the k samples are not derived from the same population. Because of the latter, there is a high likelihood that the magnitude of the scores in one distribution is greater than the magnitude of the scores in the other distribution.

As is the case with the **Kruskal–Wallis one-way analysis of variance by ranks (Test 22)**, in employing the **van der Waerden normal-scores test for k independent samples**, one of the following is true with regard to the rank-order data that are evaluated: a) The data are in a rank-order format, since it is the only format in which scores are available; or b) The data have been transformed into a rank-order format from an interval/ratio format, since the researcher has reason to believe that one or more of the assumptions of the **single-factor between-subjects analysis**

of variance (**Test 21**) (which is the parametric analog of the **Kruskal–Wallis test** and the **van der Waerden test**) are saliently violated. It should be noted that when a researcher elects to transform a set of interval/ratio data into ranks, information is sacrificed. This latter fact accounts for why there is reluctance among some researchers to employ nonparametric tests such as the **Kruskal–Wallis one-way analysis of variance by ranks** and the **van der Waerden normal-scores test for k independent samples**, even if there is reason to believe that one or more of the assumptions of the **single-factor between-subjects analysis of variance** have been violated.

Conover (1980, 1999) notes that the **van der Waerden normal-scores test for k independent samples** is based on the same assumptions as the **Kruskal–Wallis one-way analysis of variance by ranks**, which are as follows: a) Each sample has been randomly selected from the population it represents; b) The k samples are independent of one another; c) The dependent variable (which is subsequently ranked) is a continuous random variable. In truth, this assumption, which is common to many nonparametric tests, is often not adhered to, in that such tests are often employed with a dependent variable that represents a discrete random variable; and d) The underlying distributions from which the samples are derived are identical in shape. The shapes of the underlying population distributions, however, do not have to be normal.

II. Example

Example 23.1 is identical to Examples 21.1/22.1 (which are respectively evaluated with the **single-factor between-subjects analysis of variance** and the **Kruskal–Wallis one-way analysis of variance by ranks**). In evaluating Example 23.1 it will be assumed that the ratio data (i.e., the number of nonsense syllables correctly recalled) are rank-ordered, since one or more of the assumptions of the **single-factor between-subjects analysis of variance** have been saliently violated.

Example 23.1 *A psychologist conducts a study to determine whether or not noise can inhibit learning. Each of 15 subjects is randomly assigned to one of three groups. Each subject is given 20 minutes to memorize a list of 10 nonsense syllables which she is told she will be tested on the following day. The five subjects assigned to **Group 1**, the **no noise** condition, study the list of nonsense syllables while they are in a quiet room. The five subjects assigned to **Group 2**, the **moderate noise** condition, study the list of nonsense syllables while listening to classical music. The five subjects assigned to **Group 3**, the **extreme noise** condition, study the list of nonsense syllables while listening to rock music. The number of nonsense syllables correctly recalled by the 15 subjects follows: **Group 1:** 8, 10, 9, 10, 9; **Group 2:** 7, 8, 5, 8, 5; **Group 3:** 4, 8, 7, 5, 7. Do the data indicate that noise influenced subjects' performance?*

III. Null versus Alternative Hypotheses

Null hypothesis H_0 : The $k = 3$ groups are derived from the same population.

(If the null hypothesis is supported, the averages of the normal-scores for each of the $k = 3$ groups will be equal (i.e., $\bar{z}_1 = \bar{z}_2 = \bar{z}_3$). If the latter is true, it indicates that the three underlying populations are equivalent with respect to the magnitude of the scores in each of the distributions.)

Alternative hypothesis H_1 : At least two of the $k = 3$ groups are not derived from the same population.

(If the alternative hypothesis is supported, the averages of the normal-scores computed for at least two of the $k = 3$ groups will not be equal to one another. It is important to note that the alternative

hypothesis does not require that $\bar{z}_1 \neq \bar{z}_2 \neq \bar{z}_3$, since the latter implies that all three normal-scores means must differ from one another. If the alternative hypothesis is supported, it indicates that at least two of the three populations are not equivalent with respect to the magnitude of the scores in each of the distributions. In this book it will be assumed (unless stated otherwise) that the alternative hypothesis for the **van der Waerden normal-scores test for k independent samples** is stated **nondirectionally**.²

IV. Test Computations

The total number of subjects employed in the experiment is $N = 15$, and there are $n_j = n_1 = n_2 = n_3 = 5$ subjects in each group. The use of the **van der Waerden normal-scores test for k independent samples** assumes that the ratio scores of the $N = 15$ subjects have been rank-ordered in accordance with the rank-ordering procedure described for the **Kruskal–Wallis one-way analysis of variance by ranks** (the aforementioned rank-ordering procedure is described in Section IV of the latter test). [Table 23.1](#) summarizes the data for Example 23.1. The table lists the following values for each of the $n_j = 5$ subjects in the $k = 3$ groups (where j indicates the j^{th} group): a) The original ratio scores of the subjects (i.e., X_j , the number of nonsense syllables correctly recalled); b) The rank-order of each score (R_j) within the framework of the rank-ordering procedure described for the **Kruskal–Wallis one-way analysis of variance by ranks**; and c) The normal score value (z_j) computed for each rank-order.

Table 23.1 Summary of Data for Example 23.1

Group 1			Group 2			Group 3		
X_1	R_1	z_1	X_2	R_2	z_2	X_3	R_3	z_3
8	9.5	.24	7	6	-.32	4	1	-1.53
10	14.5	1.32	8	9.5	.24	8	9.5	.24
9	12.5	.78	5	3	-.89	7	6	-.32
10	14.5	1.32	8	9.5	.24	5	3	-.89
9	12.5	.78	5	3	-.89	7	6	-.32
$\Sigma z_1 = 4.44$			$\Sigma z_2 = -1.62$			$\Sigma z_3 = -2.82$		
$\bar{z}_1 = .888$			$\bar{z}_2 = -.324$			$\bar{z}_3 = -.564$		

As noted above, in order to conduct the **van der Waerden normal-scores test for k independent samples**, each of the rank-orders must be converted into a normal score. Since the latter conversion is based on cumulative proportions (or percentiles) for the normal distribution, at this point in the discussion the reader may want to review the following material: a) The material in the **Introduction** on percentiles and cumulative proportions (within the context of a cumulative frequency distribution), and the material on the normal distribution; and b) The material on cumulative proportions in Section I of the **Kolmogorov–Smirnov goodness-of-fit test for a single sample**.

The following protocol is employed to convert a rank-order into a normal score: Divide the rank-order by the value $(N + 1)$. The resulting value will be a proportion (which will be designated as P) that is greater than 0 but less than 1. The proportion that is computed is conceptualized as the percentile for that score (when the decimal point is moved two places to the right). The standard normal score (i.e., z value) which corresponds to that percentile will represent the normal score for that rank-order. The latter z value is obtained through use of [Table A1 \(Table of the Normal Distribution\)](#) in the **Appendix**.

To illustrate, the computation of the normal score of $z = .24$ for Subject 1 in Group 1 will now be explained. The original score for the subject in question is 8, which is assigned a rank-

order of 9.5 within the framework of the **Kruskal–Wallis** ranking procedure. Employing the procedure described above for converting a rank-order into a proportion, the rank-order 9.5 is divided by $N + 1 = 15 + 1 = 16$. Thus, $P = 9.5/16 = .5938$. The latter proportion is conceptualized as a cumulative proportion or percentile in a normal distribution (by moving the decimal point two places to the right, the proportion .5938 is converted into 59.38%). This result tells us that the normal score for the rank-order 9.5 will be the z value that corresponds to the cumulative proportion .5938 in the normal distribution (or expressed within the framework of a percentile, the z value that falls at the 59.38th percentile). The point in question corresponds to the point on the normal distribution below which 59.38% of the cases fall (or to state it proportionally, .5938 is the proportion of cases that fall below that point). Since the latter proportion/percentile is above .50/50% (i.e. above the mean of the normal distribution), **the sign of the z value will be positive**. In order to identify the appropriate z value, we look in **Column 2** of **Table A1** for the value that is closest to $.5938 - .5000 = .0938$. The latter value is $z = .24$, since the entry .0948 in **Column 2** for $z = .24$ is closest to .0938.³

The general rule for determining the normal score for any proportion (P) that is greater than .5000 is to find in **Column 2** of **Table A1** the proportion (which we will designate as Q) that is closest to the difference between the value of P and .5000 (i.e., $P - .5000 = Q$). The z value in the row that corresponds to the value of Q will be the normal score for the proportion P .

The computation of a normal score for a proportion that is less than .5000 will now be explained. To demonstrate this we will use the normal score of $z = -1.53$ for Subject 1 in Group 3. The original score for the subject in question is 4, which is assigned a rank-order of 1 within the framework of the **Kruskal–Wallis** ranking procedure. Employing the protocol for converting a rank-order into a proportion, the rank-order 1 is divided by $N + 1 = 15 + 1 = 16$. Thus, $P = 1/16 = .0625$. The latter proportion is conceptualized as a cumulative proportion or percentile in a normal distribution (by moving the decimal point two places to the right, the proportion .0625 is converted into 6.25%). This result tells us that the normal score for the rank-order 1 will be the z value that corresponds to the cumulative proportion .0625 in the normal distribution (or expressed within the framework of a percentile, the z value that falls at the 6.25th percentile). The point in question corresponds to the point on the normal distribution below which 6.25% of the cases fall (or to state it proportionally, .0625 is the proportion of cases that fall below that point). Since the latter proportion/percentile is below .50/50% (i.e. below the mean of the normal distribution), **the sign of the z value will be negative**. In order to identify the appropriate z value, we look in **Column 3** of **Table A1** for the value that is closest to .0625. The latter value is $z = 1.53$, since the entry .0630 in **Column 3** for $z = 1.53$ is closest to .0625.

The general rule for determining the normal score for any proportion (P) that is less than .5000 is to find in **Column 3** of **Table A1** the proportion that is closest to the value of P . The z value in the row that corresponds to the value of P will be the normal score for the proportion P . A negative sign is assigned to the obtained z value.

After computing a normal score for each of the 15 rank-orders in **Table 23.1**, the sum of the normal-scores is computed for each group. The latter values in **Table 23.1** are $\Sigma z_1 = 4.44$, $\Sigma z_2 = -1.62$, $\Sigma z_3 = -2.82$. An average normal score for each group is computed by dividing the sum of the normal-scores for the group by the number of subjects in the group. Thus: $\bar{z}_1 = \Sigma z_1/n_1 = 4.44/5 = .888$, $\bar{z}_2 = \Sigma z_2/n_2 = -1.62/5 = -.324$, and $\bar{z}_3 = \Sigma z_3/n_3 = -2.82/5 = -.564$. In order to compute the test statistic for the **van der Waerden normal-scores test for k independent samples**, it is necessary to compute the estimated population variance (\hat{s}^2) of the normal-scores. The latter is computed with Equation 23.1.

$$\hat{s}^2 = \frac{\sum_{j=1}^k \sum_{i=1}^n z_{ij}^2}{N - 1} \quad (\text{Equation 23.1})$$

The notation in Equation 23.1 indicates the following: a) If we let z_{ij} represents the normal score for the i^{th} subject in Group j , then $\sum_{j=1}^k \sum_{i=1}^n z_{ij}^2$ indicates that each of the N (i.e., $(k)(n) = N$)

normal-scores is squared, and the N squared normal-scores are summed; and b) The sum of the squared normal scores is divided by $(N - 1)$, which yields the value of the variance. Employing Equation 23.1, the value $\hat{s}^2 = .7482$ is computed. Conover (1980, 1999) notes that the computed value for the variance will generally be close to 1.⁴

$$\hat{s}^2 = \frac{(.24)^2 + (1.32)^2 + \dots + (-.89)^2 + (-.32)^2}{15 - 1} = .7482$$

The chi-square distribution provides an excellent estimate of the exact probability distribution for the **van der Waerden** test statistic. The chi-square estimate of the test statistic (to be designated χ_{vdw}^2) is computed with Equation 23.2.⁵

$$\chi_{vdw}^2 = \frac{\sum_{j=1}^k n_j (\bar{z}_j)^2}{\hat{s}^2} \quad (\text{Equation 23.2})$$

The notation in Equation 23.2 indicates the following: a) In the numerator of the equation, the number of subjects in each group (n_j) is multiplied by the square of the mean of the normal-scores for that group. Upon doing the latter for all k groups, the k resulting values are summed; and b) The final sum obtained in part a) is divided by the estimated population variance computed with Equation 23.1.

When Equation 23.2 is employed to compute the test statistic for the **van der Waerden normal-scores test for k independent samples**, the value $\chi_{vdw}^2 = 8.10$ is obtained.

$$\chi_{vdw}^2 = \frac{(5)(.888)^2 + (5)(-.324)^2 + (5)(-.564)^2}{.7482} = 8.10$$

V. Interpretation of the Test Results

In order to reject the null hypothesis the computed value χ_{vdw}^2 must be equal to or greater than the tabled critical chi-square value at the prespecified level of significance. The computed chi-square value is evaluated with **Table A4 (Table of the Chi-Square Distribution)** in the **Appendix**. For the appropriate degrees of freedom, the tabled $\chi_{.95}^2$ value (which is the chi-square value at the 95th percentile) and the tabled $\chi_{.99}^2$ value (which is the chi-square value at the 99th percentile) are employed as the .05 and .01 critical values for evaluating a nondirectional alternative hypothesis. The number of degrees of freedom employed in the analysis are computed with Equation 23.3. Thus, $df = 3 - 1 = 2$.

$$df = k - 1 \quad (\text{Equation 23.3})$$

For $df = 2$, the tabled critical .05 and .01 chi-square values are $\chi_{.05}^2 = 5.99$ and $\chi_{.01}^2 = 9.21$. Since the computed value $\chi_{vdw}^2 = 8.10$ is greater than $\chi_{.05}^2 = 5.99$, the alternative hypothesis is supported at the .05 level. Since, however, $\chi_{vdw}^2 = 8.10$ is less than $\chi_{.01}^2 = 9.21$,

the alternative hypothesis is not supported at the .01 level. A summary of the analysis of Example 23.1 with the **van der Waerden normal-scores test for k independent samples** follows: It can be concluded that there is a significant difference between at least two of the three groups exposed to different levels of noise. This result can be summarized as follows: $\chi_{vdw}^2(2) = 8.10, p < .05$.

It should be noted that when the data for Example 23.1 are evaluated with the **Kruskal–Wallis one-way analysis of variance by ranks**, the identical conclusions are reached (i.e., the null hypothesis can be rejected at the .05 level, but not at the .01 level — although the **Kruskal–Wallis test** results in a slightly larger chi-square value). When the data are evaluated with **single-factor between-subjects analysis of variance**, the null hypothesis can be rejected at both the .05 and .01 levels (although it barely achieves significance at the latter level). The slight discrepancy between the results of the **van der Waerden test** and the **analysis of variance** suggests that in the case of Examples 21.1/22.1/23.1, it would appear that the **analysis of variance** provides a slightly more powerful test of the alternative hypothesis than either the **van der Waerden** or **Kruskal–Wallis tests**.

VI. Additional Analytical Procedures for the van der Waerden Normal-Scores Test for k Independent Samples

1. Pairwise comparisons following computation of the test statistic for the van der Waerden normal-scores test for k independent samples Prior to reading this section the reader should review the discussion of comparisons in Section VI of the **single-factor between-subjects analysis of variance**. As is the case with the omnibus F value computed for the **single-factor between-subjects analysis of variance**, the χ_{vdw}^2 value computed with Equation 23.2 is based on an evaluation of all k groups. When the value of χ_{vdw}^2 is significant, it does not indicate whether just two or, in fact, more than two groups differ significantly from one another. In order to answer the latter question, it is necessary to conduct comparisons contrasting specific groups with one another. This section will describe a methodology that can be employed for conducting **simple/pairwise comparisons** following the computation of an χ_{vdw}^2 value.⁶

In conducting a simple comparison between any two groups to be designated a and b , the null hypothesis and nondirectional alternative hypothesis are as follows: H_0 : Groups a and b are derived from identical population distributions; H_1 : Groups a and b are not derived from identical population distributions. The alternative hypothesis can also be stated directionally insofar as the researcher can predict that the magnitude of the scores in one distribution is greater than the magnitude of the scores in the other distribution. As is the case with the omnibus null hypothesis, the decision made with regard to the null hypothesis for a comparison will be a function of the magnitude of the difference between the averages of the normal-scores for the groups that are involved in the comparison.

Conover (1980, 1999) describes the use of Equation 23.4 to conduct comparisons for the **van der Waerden normal-scores test for k independent samples**. The latter equation allows a researcher to identify the minimum required difference between the means of the normal-scores of any two groups (designated as CD_{vdw}) in order for them to differ from one another at the prespecified level of significance.

$$CD_{vdw} = t_{adj} \sqrt{\bar{s}^2 \left(\frac{N - 1 - \chi_{vdw}^2}{N - k} \right) \left(\frac{1}{n_a} + \frac{1}{n_b} \right)} \quad (\text{Equation 23.4})$$

Where: n_a and n_b represent the number of subjects in each of the groups involved in the simple comparison

The value of t_{adj} is obtained from the **Table A2 (Table of Student's t Distribution)** in the **Appendix**. In the case of a nondirectional alternative hypothesis, t_{adj} is the t value for $df = N - k$, above which a proportion of cases corresponding to the value $\alpha_{FW}/2c$ falls (where c is the total number of comparisons that are conducted). In Example 23.1, $df = 15 - 3 = 12$. In the case of a directional alternative hypothesis, t_{adj} is the t value above which a proportion of cases corresponding to the value α_{FW}/c falls. When all possible pairwise comparisons are made $c = [k(k - 1)]/2$, and thus, $2c = k(k - 1)$. In Example 23.1 the number of pairwise/simple comparisons that can be conducted are $c = [3(3 - 1)]/2 = 3$ — specifically, Group 1 versus Group 2, Group 1 versus Group 3, and Group 2 versus Group 3.

The value of t_{adj} will be a function of both the maximum **familywise Type I error rate** (α_{FW}) the researcher is willing to tolerate and the total number of comparisons that are conducted. When a limited number of comparisons are planned prior to collecting the data, most sources take the position that a researcher is not obliged to control the value of α_{FW} . In such a case, the **per comparison Type I error rate** (α_{PC}) will be equal to the prespecified value of alpha. When α_{FW} is not adjusted, the value of t_{adj} employed in Equation 23.4 will be the tabled critical t value that corresponds to the prespecified level of significance. Thus, if a nondirectional alternative hypothesis is employed and $\alpha = \alpha_{PC} = .05$, for $df = 12$, the tabled critical two-tailed .05 value $t_{.05} = 2.179$ is used to represent t_{adj} in Equation 23.4. If $\alpha = \alpha_{PC} = .01$, the tabled critical two-tailed .01 value $z_{.01} = 3.055$ is used in Equation 23.4. In the same respect, if a directional alternative hypothesis is employed, the tabled critical .05 and .01 one-tailed values $t_{.05} = 1.782$ and $t_{.01} = 2.681$ are used for t_{adj} in Equation 23.4.

When comparisons are not planned beforehand, it is generally acknowledged that the value of α_{FW} must be controlled so as not to become excessive. The general approach for controlling the latter value is to establish a **per comparison Type I error rate** which insures that α_{FW} will not exceed some maximum value stipulated by the researcher. One method for doing this (described under the **single-factor between-subjects analysis of variance** as the **Bonferroni-Dunn method**) establishes the **per comparison Type I error rate** by dividing the maximum value one will tolerate for the **familywise Type I error rate** by the total number of comparisons conducted. Thus, in Example 23.1, if one intends to conduct all three pairwise comparisons and wants to insure that α_{FW} does not exceed .05, $\alpha_{PC} = \alpha_{FW}/c = .05/3 = .0167$. The latter proportion is used to determine the value of t_{adj} . As noted earlier, if a directional alternative hypothesis is employed for a comparison, the value of t_{adj} employed in Equation 23.4 is the t value above which a proportion equal to $\alpha_{PC} = \alpha_{FW}/c$ of the cases falls. In **Table A2**, by interpolation (since the exact value is not listed) the t value that corresponds approximately to the proportion .0167 (for $df = 12$) is $t = 2.35$. By employing $t_{\text{adj}} = 2.35$ in Equation 23.4, one can be assured that within the “family” of three pairwise comparisons, α_{FW} will not exceed .05 (assuming all of the comparisons are directional). If a nondirectional alternative hypothesis is employed for all of the comparisons, the value of t_{adj} will be the t value above which a proportion equal to $\alpha_{FW}/2c = \alpha_{PC}/2$ of the cases falls. Since $\alpha_{PC}/2 = .0167/2 = .0083$, $t = 2.75$. By employing $t_{\text{adj}} = 2.75$ in Equation 23.4, one can be assured that α_{FW} will not exceed .05.⁷

In order to employ the CD_{vdw} value computed with Equation 23.4, it is necessary to determine the mean normal score for each of the k groups (which we have already done), and then compute the absolute value of the difference between the mean normal-scores of each pair of groups that are compared.⁸ In **Table 23.1** the following values for the mean normal-scores of the groups are computed: $\bar{z}_1 = .888$, $\bar{z}_2 = -.324$, $\bar{z}_3 = -.564$. Employing the latter values, **Table 23.2** summarizes the difference scores between pairs of mean normal-scores.

Table 23.2 Difference Scores Between Pairs of Mean Normal-Scores for Example 23.1

$ \bar{z}_1 - \bar{z}_2 = .888 - (-.324) = 1.212$
$ \bar{z}_1 - \bar{z}_3 = .888 - (-.564) = 1.452$
$ \bar{z}_2 - \bar{z}_3 = (-.324) - (-.564) = .24$

If any of the differences between mean normal-scores is equal to or greater than the CD_{vdw} value computed with Equation 23.4, a comparison is declared significant. Equation 23.4 will now be employed to evaluate the nondirectional alternative hypothesis for all three pairwise comparisons. Since it will be assumed that the comparisons are unplanned and that the researcher does not want the value of α_{FW} to exceed .05, the value $t_{adj} = 2.75$ will be used in computing CD_{vdw} .

$$CD_{vdw} = (2.75) \sqrt{(.7482) \left(\frac{15 - 1 - 8.10}{15 - 3} \right) \left(\frac{1}{5} + \frac{1}{5} \right)} = (2.75)(.3836) = 1.055$$

The obtained value $CD_{vdw} = 1.055$ indicates that any difference between the mean normal-scores of two groups that is equal to or greater than 1.055 is significant. With respect to the three pairwise comparisons, the differences $|\bar{z}_1 - \bar{z}_2| = 1.212$ and $|\bar{z}_1 - \bar{z}_3| = 1.452$ are greater than $CD_{vdw} = 1.055$. Thus, we can conclude there is a significant difference between the performance of Group 1 and Group 2 and between the performance of Group 1 and Group 3.⁹

The same logic employed for computing a confidence interval for a comparison described in Section VI of the **single-factor between-subjects analysis of variance** can be employed to compute a confidence interval for the **van der Waerden** test model. Specifically: Add to and subtract the computed value of CD_{vdw} from the obtained difference between the two mean normal-scores involved in a comparison. Thus, $CI_{.95}$ (based on $\alpha_{FW} = .05$) for the comparison Group 1 versus Group 2 is computed as follows: $CI_{.95} = 1.212 \pm 1.055$. In other words, the researcher can be 95% confident (or the probability is .95) that the mean of the normal-scores in the population represented by Group 1 is between .157 and 2.267 standard deviation units larger than the mean of the normal-scores in the population represented by Group 2.

VII. Additional Discussion of the van der Waerden Normal-Scores Test for k Independent Samples

1. Alternative normal-scores tests Alternative normal-scores procedures have been developed Terry and Hoeffding (Terry (1952)) and Bell and Doksum (1965). The latter procedures are described in Marascuilo and McSweeney (1977), who also discuss the extension of normal-scores tests to other experimental designs (e.g., repeated measures/matched-samples designs). The alternative normal-scores tests employ a different procedure from the one described for the **van der Waerden test** for determining a normal score for each of the rank-orders in a sample. For example, the **Bell–Doksum normal-scores test** (1965) obtains N random normal deviates (which are typically generated with a pseudorandom number generator, which is discussed in Section IX (the **Addendum**) of the **single-sample runs test (Test 10)**), ordinarily arranges the N random normal deviates (i.e., the N z scores), and then pairs each of the random deviates (z scores) with the rank-order in the same ordinal position.

VIII. Additional Examples Illustrating the van der Waerden Normal-Scores test for k Independent Samples

The **van der Waerden normal-scores test for k independent samples** can be employed to evaluate any of the additional examples noted for the **single-factor between-subjects analysis of variance**, if the data for the latter examples are rank-ordered, and the rank-orders are then converted into normal-scores. The **van der Waerden test** can also be employed to evaluate Examples 22.2 and 22.3, which are presented in Section VIII of the **Kruskal–Wallis one-way analysis of variance by ranks**.

As noted earlier, the **van der Waerden normal-scores test for k independent samples** can be employed to evaluate a design involving $k = 2$ independent samples/groups. Thus, the test can be used to evaluate the data for any of the examples noted for the **t test for two independent samples (Test 11)** and the **Mann–Whitney U test (Test 12)** (assuming the interval/ratio scores are rank-ordered, and the ranks are then converted into normal-scores). Example 23.2 is identical to Example 11.1/12.1, which is employed to illustrate the use of the **t test for two independent samples** and the **Mann–Whitney U test**. The example will be employed to illustrate the use of the **van der Waerden normal-scores test for k independent samples** when there are $k = 2$ independent samples/groups.

Example 23.2 *In order to assess the efficacy of a new antidepressant drug, ten clinically depressed patients are randomly assigned to one of two groups. Five patients are assigned to Group 1, which is administered the antidepressant drug for a period of six months. The other five patients are assigned to Group 2, which is administered a placebo during the same six-month period. Assume that prior to introducing the experimental treatments, the experimenter confirmed that the level of depression in the two groups was equal. After six months elapse, all ten subjects are rated by a psychiatrist (who is blind with respect to a subject's experimental condition) on their level of depression. The psychiatrist's depression ratings for the five subjects in each group follow (the higher the rating, the more depressed a subject): **Group 1:** 11, 1, 0, 2, 0; **Group 2:** 11, 11, 5, 8, 4. Do the data indicate that the antidepressant drug is effective?*

Table 23.3 summarizes the analysis of the data with the **van der Waerden normal-scores test for k independent samples**. The null hypothesis evaluated with the test is: H_0 : The $k = 2$ groups are derived from the same population. The nondirectional alternative hypothesis evaluated with the test is: H_1 : The $k = 2$ groups are not derived from the same population. If a directional alternative hypothesis is employed, it will predict that the two groups are derived from different populations, but more specifically, that the magnitude of the scores in Group 2 will be larger than the magnitude of the scores in Group 1.

The computed value for the **van der Waerden test statistic** is $\chi^2_{vdw} = 3.16$. Since $k = 2$, $df = 2 - 1 = 1$. Employing **Table A4**, we determine that for $df = 1$, the tabled critical two-tailed values that are employed to evaluate a nondirectional alternative hypothesis are $\chi^2_{.05} = 3.84$ and $\chi^2_{.01} = 6.63$. Since the computed value $\chi^2_{vdw} = 3.16$ is less than $\chi^2_{.05} = 3.84$, the nondirectional alternative hypothesis is not supported at the .05 level. The tabled critical one-tailed values that are employed for evaluating a directional alternative hypothesis are $\chi^2_{.05} = 2.71$ and $\chi^2_{.01} = 5.10$.¹⁰ Since the computed value $\chi^2_{vdw} = 3.16$ is greater than $\chi^2_{.05} = 2.71$, but less than $\chi^2_{.01} = 5.10$, the directional alternative hypothesis predicting that Group 1 (the group that received the drug) will have a lower level of depression is supported at the .05 level, but not at the .01 level. This result is consistent with that obtained when the same data are evaluated with the **t test for two independent samples** and the **Mann–Whitney U test** — in other words, in the case of the latter tests, the same directional alternative hypothesis is supported, but only at the .05 level.

Table 23.3 Summary of Data for Example 23.2

Group 1			Group 2		
X_1	R_1	z_1	X_2	R_2	z_2
11	9	.91	11	9	.91
1	3	-.60	11	9	.91
0	1.5	-1.10	5	6	.11
2	4	-.35	8	7	.35
0	1.5	-1.10	4	5	-.11
$\Sigma z_1 = -2.24$			$\Sigma z_2 = 2.17$		
$\bar{z}_1 = -.448$			$\bar{z}_2 = .434$		
$s^2 = \frac{(.91)^2 + (-.60)^2 + + (.35)^2 + (-.11)^2}{10 - 1} = .6148$					
$\chi^2_{vdw} = \frac{(5)(-.448)^2 + (5)(.434)^2}{.6148} = 3.16$					

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Endnotes

1. Conover (1980, 1999) and Marascuilo and McSweeney (1977) note that normal-scores tests have equal or greater power than their parametric analogs. The latter sources state that the **asymptotic relative efficiency** (which is discussed in Section VII of the **Wilcoxon signed-ranks test (Test 6)**) of a normal-scores test is equal to 1 when the underlying population distribution(s) are normal, and often greater than 1 when the underlying population distribution(s) are something other than normal. What the latter translates into is that for a given

level of power, a normal-scores test will require an equal number or even fewer subjects than the analogous parametric test in evaluating an alternative hypothesis.

2. Although it is possible to conduct a directional analysis when $k \geq 3$, such an analysis will not be described with respect to the **van der Waerden normal-scores test for k independent samples**. A discussion of a directional analysis when $k = 2$ can be found in Section VIII where the **van der Waerden test** is employed to evaluate the data for Examples 11.1/12.1 (which are employed to illustrate the **t test for two independent samples** and the **Mann–Whitney U test**). A discussion of the evaluation of a directional alternative hypothesis when $k \geq 3$ can be found in Section VII of the **chi-square goodness-of-fit test (Test 8)**. Although the latter discussion is in reference to analysis of a k independent samples design involving categorical data, the general principles regarding analysis of a directional alternative hypothesis when $k \geq 3$ are applicable to the **van der Waerden normal-scores test for k independent samples**.
3. The proportion of cases in the normal distribution that fall below the mean is .5000. The value .0948 in **Column 2** represents the proportion of cases that fall between the mean and the value $z = .24$. Thus, $.5000 + .0948 = .5948$ represents to proportion of cases that fall below the value $z = .24$.
4. Conover (1980, 1999) notes that if there are no ties, the mean of the $N z_{ij}$ scores (i.e., the mean of all N normal-scores) will equal zero, and be extremely close to zero when there are ties. Thus, if the mean equals zero, the equation $\hat{s}^2 = \sum(X - \bar{X})^2/(n - 1)$ (which is Equation I.5, the definitional equation for computing the unbiased estimate of a population variance) reduces to $\hat{s}^2 = \sum X^2/(n - 1)$. If z is employed in place of X and N in place of n (since in Equation 23.1 the variance of $N z$ scores is computed), we obtain Equation 23.1, $\hat{s}^2 = \sum z_{ij}^2/(N - 1)$.
5. When two or more groups do not have the same sample size, the value of n_j for a given group is used to represent the group sample size in any of the equations that require the group sample size.
6. In the discussion of comparisons under the **single-factor between-subjects analysis of variance**, it is noted that a **simple** (also known as a **pairwise**) **comparison** is a comparison between any two groups in a set of k groups.
7. The rationale for the use of the proportions .0167 and .0083 is explained more thoroughly in Endnote 5 of the **Kruskal–Wallis one-way analysis of variance**. In the case of the latter test, since the normal distribution is employed in the comparison procedure, the explanation of the proportions is in reference to a standard normal deviate (i.e., a z value). The same rationale applies when the t distribution is employed, with the only difference being that for a corresponding probability level, the t values that are used are different than the z values employed for the **Kruskal–Wallis** comparison procedure.

The values $t_{.0167} = 2.35$ and $t_{.0083} = 2.75$ are based on interpolating the t values in **Table A2** (since exact values are not listed for $t_{.0167}$ and $t_{.0083}$). The value $t_{.0167} = 2.35$ is the best estimate of the t value at the 98.33th percentile (since $1 - .9833 = .0167$). The value $t_{.0083} = 2.75$ is the best estimate of the t value at the 99.17th percentile (since $1 - .9917 = .0083$).

8. It should be noted that when a directional alternative hypothesis is employed, the sign of the difference between the two mean normal-scores must be consistent with the prediction stated in the directional alternative hypothesis. When a nondirectional alternative hypothesis is employed, the direction of the difference between two mean normal-scores is irrelevant.
9. Equation 23.4 is analogous to Equation 22.6, which Conover (1980, 1999) employs in conducting a comparison for the **Kruskal–Wallis one-way analysis of variance**. If the element $[(N - 1 - \chi^2_{vdw}) / (N - k)]$ is omitted from the radical in Equation 23.4, it becomes Equation 23.5, which is analogous to Equation 22.5. Equation 23.5 will yield a larger CD_{vdw} value than Equation 23.4. It is demonstrated below that when Equation 23.5 is employed with the data for Example 23.1, the value $CD_{vdw} = 1.504$ is obtained. If the latter CD_{vdw} value is employed, none of the pairwise comparisons are significant, since no difference is equal to or greater than 1.504. As noted in the discussion of comparisons in the **Kruskal–Wallis one-way analysis of variance**, an equation in the form of Equation 23.5 conducts a less powerful/ more conservative comparison.

(Equation 23.5)

$$CD_{vdw} = t_{adj} \sqrt{s^2 \left(\frac{1}{n_a} + \frac{1}{n_b} \right)} = (2.75) \sqrt{(.7482) \left(\frac{1}{5} + \frac{1}{5} \right)} = 1.504$$

In Section VI of the **Kruskal–Wallis one-way analysis of variance** it is noted that sources do not agree on the methodology for conducting pairwise comparisons for the latter test. The general comments regarding comparisons for the **Kruskal–Wallis test** can be extended to the **van der Waerden normal-scores test for k independent samples** (since sources do not agree on the comparison protocol for the **van der Waerden test**). Thus, if two or more methods for conducting comparisons yield dramatically different results for a specific comparison, one or more replication studies employing reasonably large sample sizes should clarify whether or not an obtained difference is reliable, as well as the magnitude of the difference (if, in fact, one exists).

10. The tabled critical one-tailed .05 and .01 values are, respectively, the tabled chi-square values at the 90th and 98th percentiles/quantiles of the chi-square distribution. For clarification regarding the latter values, the reader should review the material on the evaluation of a directional hypothesis involving the chi-square distribution in Section VII of the **chi-square goodness-of-fit test**, and the discussion of **Table A4** in Section IV of the **single-sample chi-square test for a population variance (Test 3)**. Since the chi-square value at the 98th percentile is not in **Table A4**, the value $\chi^2_{.01} = 5.10$ is an approximation of the latter value.

Inferential Statistical Tests Employed with Two or More Dependent Samples (and Related Measures of Association/Correlation)

**Test 24: The Single-Factor Within-Subjects Analysis
of Variance**

**Test 25: The Friedman Two-Way Analysis of Variance
by Ranks**

Test 26: The Cochran Q Test

Test 24

The Single-Factor Within-Subjects Analysis of Variance (Parametric Test Employed with Interval/Ratio Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test In a set of k dependent samples (where $k \geq 2$), do at least two of the samples represent populations with different mean values?

Relevant background information on test Prior to reading this section the reader should review the general comments on the analysis of variance in Section I of the **single-factor between-subjects analysis of variance (Test 21)**. In addition, the general information regarding a dependent samples design contained in Sections I and VII of the **t test for two dependent samples (Test 17)** should be reviewed. The **single-factor within-subjects analysis of variance** (which is also referred to as the **single-factor repeated-measures analysis of variance** and the **randomized-blocks one-way analysis of variance**)¹ is employed in a hypothesis testing situation involving k dependent samples. In contrast to the **t test for two dependent samples**, which only allows for a comparison of the means of two dependent samples, the **single-factor within-subjects analysis of variance** allows for comparison of two or more dependent samples. When the number of dependent samples is $k = 2$, the **single-factor within-subjects analysis of variance** and the **t test for two dependent samples** yield equivalent results.

In conducting the **single-factor within-subjects analysis of variance**, each of the k sample means is employed to estimate the value of the mean of the population the sample represents. If the computed test statistic is significant, it indicates there is a significant difference between at least two of the sample means in the set of k means. As a result of the latter, the researcher can conclude there is a high likelihood that at least two of the samples represent populations with different mean values.

In order to compute the test statistic for the **single-factor within-subjects analysis of variance**, the following two variability components (which are part of the **total variability**) are contrasted with one another: **between-conditions variability** and **residual variability**. **Between-conditions variability** (which is also referred to as **treatment variability**) is essentially a measure of the variance of the means of the k experimental conditions. **Residual variability** is the amount of variability within the k scores of each of the n subjects which cannot be accounted for on the basis of a treatment effect. **Residual variability** is viewed as variability that results from chance factors that are beyond the control of a researcher, and since chance factors are often referred to as experimental error, **residual variability** is also referred to as **error variability**. The **F ratio**, which is the test statistic for the **single-factor within-subjects analysis of variance**, is obtained by dividing **between-conditions variability** by **residual variability**. Since **residual variability** is employed as a baseline measure of the variability in a set of data that is beyond a researcher's control, it is assumed that if the k experimental conditions represent populations with the same mean value, the amount of variability between the means of the k experimental conditions (i.e., **between-conditions variability**) will be approximately the same

value as the **residual variability**. If, on the other hand, **between-conditions variability** is significantly larger than **residual variability** (in which case the value of the F ratio will be larger than 1), it is likely that something in addition to chance factors is contributing to the amount of variability between the means of the experimental conditions. In such a case, it is assumed that whatever it is that differentiates the experimental conditions from one another (i.e., the independent variable/experimental treatments) accounts for the fact that **between-conditions variability** is larger than **residual variability**.² A thorough discussion of the logic underlying the **single-factor within-subjects analysis of variance** can be found in Section VII.

The **single-factor within-subjects analysis of variance** is employed with interval/ratio data and is based on the following assumptions: a) The sample of n subjects has been randomly selected from the population it represents; b) The distribution of data in the underlying populations each of the experimental conditions represents is normal; and c) The third assumption, which is referred to as the **sphericity assumption**, is the analog of the homogeneity of variance assumption of the **single-factor between-subjects analysis of variance**. The assumption of sphericity, which is mathematically more complex than the homogeneity of variance assumption, essentially revolves around the issue of whether or not the underlying population variances and covariances are equal. A full discussion of the sphericity assumption (as well as the concept of covariance) can be found in Section VI. It should also be noted that the **single-factor within-subjects analysis of variance** is more sensitive to violations of its assumptions than is the **single-factor between-subjects analysis of variance**.

As is the case for the t test for two dependent samples, in order for the **single-factor within-subjects analysis of variance** to generate valid results the following guidelines should be adhered to: a) In order to control for order effects, the presentation of the k experimental conditions should be random or, if appropriate, be counterbalanced;³ and b) If matched samples are employed, within each set of matched subjects each of the subjects should be randomly assigned to one of the k experimental conditions.

As is the case with the t test for dependent samples, when $k = 2$ the **single-factor within-subjects analysis of variance** can be employed to evaluate a **before-after design**, as well as extensions of the latter design that involve more than two measurement periods. The limitations of the **before-after design** (which are discussed in Section VII of the t test for dependent samples) are also applicable when it is evaluated with the **single-factor within-subjects analysis of variance**.

The reader should take note of the fact that there are certain advantages associated with employing a within-subjects design as opposed to a between-subjects design. If within-subjects and between-subjects designs that evaluate the same hypothesis and involve the same number of scores in each of the experimental conditions are compared with one another, the number of subjects required for the within-subjects analysis is a fraction (specifically, $1/k^{th}$) of the number required for the between-subjects analysis. Another advantage of a within-subjects analysis is that it provides for a more powerful test of an alternative hypothesis. The latter can be attributed to the fact that the error variability associated with a within-subjects analysis is less than that associated with a between-subjects analysis. In spite of the aforementioned advantages of employing a within-subjects design, the between-subjects design is more commonly employed in research, since in many experiments it is impractical for a subject to serve in more than one experimental condition.

II. Example

Example 24.1 *A psychologist conducts a study to determine whether or not noise can inhibit learning. Each of six subjects is tested under three experimental conditions. In each of the*

experimental conditions a subject is given 20 minutes to memorize a list of 10 nonsense syllables, which the subject is told she will be tested on the following day. The three experimental conditions each subject serves under are as follows: **Condition 1**, the **no noise** condition, requires subjects to study the list of nonsense syllables in a quiet room. **Condition 2**, the **moderate noise** condition, requires subjects to study the list of nonsense syllables while listening to classical music. **Condition 3**, the **extreme noise** condition, requires subjects to study the list of nonsense syllables while listening to rock music. Although in each of the experimental conditions subjects are presented with a different list of nonsense syllables, the three lists are comparable with respect to those variables that are known to influence a person's ability to learn nonsense syllables. To control for order effects, the order of presentation of the three experimental conditions is completely counterbalanced.⁴ The number of nonsense syllables correctly recalled by the six subjects under the three experimental conditions follows. (Subjects' scores are listed in the order **Condition 1, Condition 2, Condition 3.**) **Subject 1:** 9, 7, 4; **Subject 2:** 10, 8, 7; **Subject 3:** 7, 5, 3; **Subject 4:** 10, 8, 7; **Subject 5:** 7, 5, 2; **Subject 6:** 8, 6, 6. Do the data indicate that noise influenced subjects' performance?

III. Null versus Alternative Hypotheses

Null hypothesis

$$H_0: \mu_1 = \mu_2 = \mu_3$$

(The mean of the population Condition 1 represents equals the mean of the population Condition 2 represents equals the mean of the population Condition 3 represents.)

Alternative hypothesis

$$H_1: \text{Not } H_0$$

(This indicates that there is a difference between at least two of the $k = 3$ population means. It is important to note that the alternative hypothesis should not be written as follows: $H_1: \mu_1 \neq \mu_2 \neq \mu_3$. The reason why the latter notation for the alternative hypothesis is incorrect is because it implies that all three population means must differ from one another in order to reject the null hypothesis. In this book it will be assumed (unless stated otherwise) that the alternative hypothesis for the analysis of variance is stated **nondirectionally**.⁵ In order to reject the null hypothesis, the obtained F value must be equal to or greater than the tabled critical F value at the prespecified level of significance.)

IV. Test Computations

The test statistic for the **single-factor within-subjects analysis of variance** can be computed with either **computational** or **definitional equations**. Although definitional equations reveal the underlying logic behind the analysis of variance, they involve considerably more calculations than do the computational equations. Because of the latter, computational equations will be employed in this section to demonstrate the computation of the test statistic. The definitional equations for the **single-factor within-subjects analysis of variance** are described in Section VII.

The data for Example 24.1 are summarized in [Table 24.1](#). In [Table 24.1](#) the $k = 3$ scores of the $n = 6$ subjects in Conditions 1, 2, and 3 are, respectively, listed in the columns labelled X_1 , X_2 , and X_3 . The notation n is employed to represent the number of scores in each of the experimental conditions. Since there are $n = 6$ scores in each condition, $n = n_1 = n_2 = n_3 = 6$. The columns labelled X_1^2 , X_2^2 , and X_3^2 list the squares of the scores of the six subjects in each of the three experimental conditions. The last column labelled $\sum S_i$ lists for each of the six subjects the sum of a subject's $k = 3$ scores. Thus, the value $\sum S_i$ is the sum of the scores for Subject i under Conditions 1, 2, and 3.

Table 24.1 Data for Example 24.1

	Condition 1		Condition 2		Condition 3		ΣS_i
	X_1	X_1^2	X_2	X_2^2	X_3	X_3^2	
Subject 1	9	81	7	49	4	16	20
Subject 2	10	100	8	64	7	49	25
Subject 3	7	49	5	25	3	9	15
Subject 4	10	100	8	64	7	49	25
Subject 5	7	49	5	25	2	4	14
Subject 6	8	64	6	36	6	36	20
<hr/>							
	$\Sigma X_1 = 51$	$\Sigma X_1^2 = 443$	$\Sigma X_2 = 39$	$\Sigma X_2^2 = 263$	$\Sigma X_3 = 29$	$\Sigma X_3^2 = 163$	$\Sigma X_T = 119$
<hr/>							
	$\bar{X}_1 = \frac{\Sigma X_1}{n_1} = \frac{51}{6} = 8.5$		$\bar{X}_2 = \frac{\Sigma X_2}{n_2} = \frac{39}{6} = 6.5$		$\bar{X}_3 = \frac{\Sigma X_3}{n_3} = \frac{29}{6} = 4.83$		
<hr/>							

The notation N represents the total number of scores in the experiment. Since there are $n = 6$ subjects and each subject has $k = 3$ scores, there are a total of $nk = N = (6)(3) = 18$ scores. The value ΣX_T represents the sum of the $N = 18$ scores (i.e., the total sum of scores). Thus:

$$\Sigma X_T = \Sigma X_1 + \Sigma X_2 + \cdots + \Sigma X_k$$

Since there are $k = 3$ experimental conditions, $\Sigma X_T = 119$.

$$\Sigma X_T = \Sigma X_1 + \Sigma X_2 + \Sigma X_3 = 51 + 39 + 29 = 119$$

The value ΣX_T can also be computed by adding up the ΣS_i scores computed for the n subjects. Thus:

$$\begin{aligned}\Sigma X_T &= \Sigma S_1 + \Sigma S_2 + \cdots + \Sigma S_n \\ \Sigma X_T &= \Sigma S_1 + \Sigma S_2 + \Sigma S_3 + \Sigma S_4 + \Sigma S_5 + \Sigma S_6 \\ &= 20 + 25 + 15 + 25 + 14 + 20 = 119\end{aligned}$$

\bar{X}_T represents the grand mean, where $\bar{X}_T = \Sigma X_T / N$. Thus, $\bar{X}_T = 119 / 18 = 6.61$. Although \bar{X}_T is not employed in the computational equations to be described in this section, it is employed in some of the definitional equations described in Section VII.

The value ΣX_T^2 represents the total sum of the N squared scores. Thus:

$$\Sigma X_T^2 = \Sigma X_1^2 + \Sigma X_2^2 + \cdots + \Sigma X_k^2$$

Since there are $k = 3$ experimental conditions, $\Sigma X_T^2 = 869$.

$$\Sigma X_T^2 = \Sigma X_1^2 + \Sigma X_2^2 + \Sigma X_3^2 = 443 + 263 + 163 = 869$$

Although the means for each of the experimental conditions are not required for computing the analysis of variance test statistic, it is recommended that they be computed since visual inspection of the condition means can provide the researcher with a general idea of whether or not it is reasonable to expect a significant result. To be more specific, if two or more of the condition means are far removed from one another, it is likely that the analysis of variance will

be significant (especially if there are a relatively large number of subjects employed in the experiment). Another reason for computing the condition means is that they are required for comparing individual conditions with one another, which is something that is often done following the analysis of variance on the full set of data. The latter types of comparisons are described in Section VI.

In order to compute the test statistic for the **single-factor within-subjects analysis of variance**, the **total variability** in the data is divided into a number of different components. Specifically, the following variability components are computed: a) The **total sum of squares** which is represented by the notation SS_T ; b) The **between-conditions sum of squares** which is represented by the notation SS_{BC} . The **between-conditions sum of squares** is the numerator of the equation that represents **between-conditions variability** (i.e., the equation that represents the amount of variability between the means of the k conditions); c) The **between-subjects sum of squares** is represented by the notation SS_{BS} . The **between-subjects sum of squares** is the numerator of the equation that represents **between-subjects variability**, which is the amount of variability between the mean scores of the n subjects (the mean of each subject being the average of a subject's k scores); and d) The **residual sum of squares** is represented by the notation SS_{res} . The **residual sum of squares** is the numerator of the equation that represents **residual variability** (i.e., error variability that is beyond the researcher's control).

Equation 24.1 describes the relationship between SS_T , SS_{BC} , SS_{BS} , and SS_{res} .⁶

$$SS_T = SS_{BC} + SS_{BS} + SS_{res} \quad (\text{Equation 24.1})$$

Equation 24.2 is employed to compute SS_T .

$$SS_T = \sum X_T^2 - \frac{(\sum X_T)^2}{N} \quad (\text{Equation 24.2})$$

Employing Equation 24.2, the value $SS_T = 82.28$ is computed.

$$SS_T = 869 - \frac{(119)^2}{18} = 869 - 786.72 = 82.28$$

Equation 24.3 is employed to compute SS_{BC} . In Equation 24.3 the notation $\sum X_j$ represents the sum of the n scores in the j^{th} condition. Note that in Equation 24.3 the notation n_j can be employed in place of n , since there are $n = n_j$ scores in the j^{th} condition.

$$SS_{BC} = \sum_{j=1}^k \left[\frac{(\sum X_j)^2}{n} \right] - \frac{(\sum X_T)^2}{N} \quad (\text{Equation 24.3})$$

The notation $\sum_{j=1}^k [(\sum X_j)^2 / n]$ in Equation 24.3 indicates that for each condition the value $(\sum X_j)^2 / n$ is computed, and the latter values are summed for all k conditions.

With reference to Example 24.1, Equation 24.3 can be rewritten as follows:

$$SS_{BC} = \left[\frac{(\sum X_1)^2}{n} + \frac{(\sum X_2)^2}{n} + \frac{(\sum X_3)^2}{n} \right] - \frac{(\sum X_T)^2}{N}$$

Substituting the appropriate values from Example 24.1 in Equation 24.3, the value $SS_{BC} = 40.45$ is computed.⁷

$$SS_{BC} = \left[\frac{(51)^2}{6} + \frac{(39)^2}{6} + \frac{(29)^2}{6} \right] - \frac{(119)^2}{18} = 827.17 - 786.72 = 40.45$$

Equation 24.4 is employed to compute SS_{BS} .

$$SS_{BS} = \sum_{i=1}^n \left[\frac{(\sum S_i)^2}{k} \right] - \frac{(\sum X_T)^2}{N} \quad (\text{Equation 24.4})$$

The notation $\sum_{i=1}^n [(\sum S_i)^2/k]$ in Equation 24.4 indicates that for each subject the value $(\sum S_i)^2/k$ is computed, and the latter values are summed for all n subjects. With reference to Example 24.1, Equation 24.4 can be rewritten as follows:

$$SS_{BS} = \left[\frac{(\sum S_1)^2}{k} + \frac{(\sum S_2)^2}{k} + \frac{(\sum S_3)^2}{k} + \frac{(\sum S_4)^2}{k} + \frac{(\sum S_5)^2}{k} + \frac{(\sum S_6)^2}{k} \right] - \frac{(\sum X_T)^2}{N}$$

Substituting the appropriate values from Example 24.1 in Equation 24.4, the value $SS_{BS} = 36.93$ is computed.⁸

$$SS_{BS} = \left[\frac{(20)^2}{3} + \frac{(25)^2}{3} + \frac{(15)^2}{3} + \frac{(25)^2}{3} + \frac{(14)^2}{3} + \frac{(20)^2}{3} \right] - \frac{(119)^2}{18} = 823.65 - 786.72 = 36.93$$

By algebraically transposing the terms in Equation 24.1, the value of SS_{res} can be computed with Equation 24.5.

$$SS_{\text{res}} = SS_T - SS_{BC} - SS_{BS} \quad (\text{Equation 24.5})$$

Employing Equation 24.5, the value $SS_{\text{res}} = 4.9$ is computed.

$$SS_{\text{res}} = 82.28 - 40.45 - 36.93 = 4.9$$

Equation 24.6 is a computationally more complex equation for computing the value of SS_{res} .

$$SS_{\text{res}} = \sum X_T^2 - \sum_{j=1}^k \left[\frac{(\sum X_j)^2}{n} \right] - \sum_{i=1}^n \left[\frac{(\sum S_i)^2}{k} \right] + \frac{(\sum X_T)^2}{N} \quad (\text{Equation 24.6})$$

Since $\sum X_T^2 = 869$, $\sum_{j=1}^k [(\sum X_j)^2/n] = 827.17$, $\sum_{i=1}^n [(\sum S_i)^2/k] = 823.65$, and $(\sum X_T)^2/N = 786.72$, employing Equation 24.6, the value $SS_{\text{res}} = 4.9$ is computed.

$$SS_{\text{res}} = 869 - 827.17 - 823.65 + 786.72 = 4.9$$

The reader should take note of the fact that the values SS_T , SS_{BC} , SS_{BS} , and SS_{res} must always be positive numbers. If a negative value is obtained for any of the aforementioned values, it indicates a computational error has been made.

At this point the values of the **between-conditions variance**, **between-subjects variance**, and the **residual variance** can be computed. In the **single-factor within-subjects analysis of variance**, the **between-conditions variance** is referred to as the **mean square between-**

conditions, which is represented by the notation MS_{BC} . MS_{BC} is computed with Equation 24.7.

$$MS_{BC} = \frac{SS_{BC}}{df_{BC}} \quad (\text{Equation 24.7})$$

The **between-subjects variance** is referred to as the **mean square between-subjects**, which is represented by the notation MS_{BS} . MS_{BS} is computed with Equation 24.8.

$$MS_{BS} = \frac{SS_{BS}}{df_{BS}} \quad (\text{Equation 24.8})$$

The **residual variance** is referred to as the **mean square residual**, which is represented by the notation MS_{res} . MS_{res} is computed with Equation 24.9.

$$MS_{\text{res}} = \frac{SS_{\text{res}}}{df_{\text{res}}} \quad (\text{Equation 24.9})$$

Note that a total mean square is not computed.

In order to compute MS_{BC} , MS_{BS} , and MS_{res} , it is required that the values df_{BC} , df_{BS} , and df_{res} (the denominators of Equations 24.7–24.9) be computed. df_{BC} , which represents the **between-conditions degrees of freedom**, are computed with Equation 24.10.

$$df_{BC} = k - 1 \quad (\text{Equation 24.10})$$

df_{BS} , which represents the **between-subjects degrees of freedom**, are computed with Equation 24.11.

$$df_{BS} = n - 1 \quad (\text{Equation 24.11})$$

df_{res} , which represents the **residual degrees of freedom**, are computed with Equation 24.12.

$$df_{\text{res}} = (n - 1)(k - 1) \quad (\text{Equation 24.12})$$

Although it is not required in order to determine the F ratio, the **total degrees of freedom** are generally computed, since it can be used to confirm the df values computed with Equations 24.10–24.12, as well as the fact it is employed in the analysis of variance summary table. The total degrees of freedom (represented by the notation df_T), are computed with Equation 24.13.

$$df_T = nk - 1 = N - 1 \quad (\text{Equation 24.13})$$

The relationship between df_{BC} , df_{BS} , df_{res} , and df_T is described by Equation 24.14.

$$df_T = df_{BC} + df_{BS} + df_{\text{res}} \quad (\text{Equation 24.14})$$

Employing Equations 24.10–24.13, the values $df_{BC} = 2$, $df_{BS} = 5$, $df_{\text{res}} = 10$, and $df_T = 17$ are computed. Note that $df_T = df_{BC} + df_{BS} + df_{\text{res}} = 2 + 5 + 10 = 17$.

$$df_{BC} = 3 - 1 = 2 \quad df_{BS} = 6 - 1 = 5$$

$$df_{res} = (6 - 1)(3 - 1) = 10 \quad df_T = 18 - 1 = 17$$

Employing Equations 24.7–24.9, the values $MS_{BC} = 20.23$, $MS_{BS} = 7.39$, and $MS_{res} = .49$ are computed.

$$MS_{BC} = \frac{40.45}{2} = 20.23 \quad MS_{BS} = \frac{36.93}{5} = 7.39 \quad MS_{res} = \frac{4.9}{10} = .49$$

The F ratio, which is the test statistic for the **single-factor within-subjects analysis of variance**, is computed with Equation 24.15.

$$F = \frac{MS_{BC}}{MS_{res}} \quad (\text{Equation 24.15})$$

Employing Equation 24.15, the value $F = 41.29$ is computed.

$$F = \frac{20.23}{.49} = 41.29$$

The reader should take note of the fact that the values MS_{BC} , MS_{BS} , and MS_{res} must always be positive numbers. If a negative value is obtained for any of the aforementioned values, it indicates a computational error has been made. If $MS_{res} = 0$, Equation 24.15 will be insoluble. If all of the conditions have the identical mean value, $MS_{BC} = 0$, and if the latter is true, $F = 0$.

V. Interpretation of the Test Results

It is common practice to summarize the results of a **single-factor within-subjects analysis of variance** with the summary table represented by [Table 24.2](#).

**Table 24.2 Summary Table of Analysis of Variance
for Example 24.1**

Source of variation	SS	df	MS	F
Between-subjects	36.93	5	7.39	
Between-conditions	40.45	2	20.23	41.29
Residual	4.90	10	.49	
Total	82.28	17		

The obtained value $F = 41.29$ is evaluated with [Table A10 \(Table of the \$F\$ Distribution\)](#) in the **Appendix**. In [Table A10](#) critical values are listed in reference to the number of degrees of freedom associated with the numerator and the denominator of the F ratio (i.e., df_{num} and df_{den}). In employing the F distribution in reference to Example 24.1, the degrees of freedom for the numerator are $df_{BC} = 2$ and the degrees of freedom for the denominator are $df_{res} = 10$. In [Table A10](#) the tabled $F_{.95}$ and $F_{.99}$ values are, respectively, employed to evaluate the non-directional alternative hypothesis H_1 : Not H_0 at the .05 and .01 levels. As is the case for the **single-factor between-subjects analysis of variance**, the notation $F_{.05}$ is employed to represent the tabled critical F value at the .05 level. The latter value corresponds to the relevant tabled

$F_{.95}$ value in [Table A10](#). In the same respect, the notation $F_{.01}$ is employed to represent the tabled critical F value at the .01 level, and corresponds to the relevant tabled $F_{.99}$ value in [Table A10](#).

For $df_{\text{num}} = 2$ and $df_{\text{den}} = 10$, the tabled $F_{.95}$ and $F_{.99}$ values are $F_{.95} = 4.10$ and $F_{.99} = 7.56$. Thus, $F_{.05} = 4.10$ and $F_{.01} = 7.56$. In order to reject the null hypothesis, the obtained F value must be equal to or greater than the tabled critical value at the prespecified level of significance. Since $F = 41.29$ is greater than both $F_{.05} = 4.10$ and $F_{.01} = 7.56$, the alternative hypothesis is supported at both the .05 and .01 levels.

A summary of the analysis of Example 24.1 with the **single-factor within-subjects analysis of variance** follows: It can be concluded that there is a significant difference between at least two of the three experimental conditions (i.e., different levels of noise). This result can be summarized as follows: $F(2,10) = 41.29, p < .01$.

VI. Additional Analytical Procedures for the Single-Factor Within-Subjects Analysis of Variance and/or Related Tests

1. Comparisons following computation of the omnibus F value for the single-factor within-subjects analysis of variance Prior to reading this section the reader should review the discussion of comparison procedures in Section VI of the **single-factor between-subjects analysis of variance**. As is the case with the latter test, the omnibus F value computed for a **single-factor within-subjects analysis of variance** is based on a comparison of the means of all k experimental conditions. Thus, in order to reject the null hypothesis, it is only required that the means of at least two of the k conditions differ significantly from one another.⁹

The same procedures that are employed for conducting comparisons for the **single-factor between-subjects analysis of variance** can be used for the **single-factor within-subjects analysis of variance**. Thus, the following comparison procedures discussed under the latter test can be employed for conducting comparisons within the framework of the **single-factor within-subjects analysis of variance**: **Test 24a: Multiple t tests/Fisher's LSD test** (which is equivalent to **linear contrasts**); **Test 24b: The Bonferroni–Dunn test**; **Test 24c: Tukey's HSD test**; **Test 24d: The Newman–Keuls test**; **Test 24e: The Scheffé test**; **Test 24f: The Dunnett test**. The only difference in applying the aforementioned comparison procedures to the analysis of variance under discussion is that a different measure of error variability is employed. Recollect that in the case of the **single-factor between-subjects analysis variance**, a pooled measure of within-groups variability (MS_{WG}) is employed as the measure of experimental error. In the case of the **single-factor within-subjects analysis of variance**, MS_{res} is employed as the measure of error variability. Consequently, in conducting comparisons for a **single-factor within-subjects analysis of variance**, MS_{res} is employed in place of MS_{WG} as the error term in the comparison equations described in Section VI of the **single-factor between-subjects analysis variance**. It should be noted, however, that if the sphericity assumption (which, as noted in Section I, is based on homogeneity of the underlying population variances and covariances) of the **single-factor within-subjects analysis of variance** is violated, MS_{res} may not provide the most accurate measure of error variability to employ in conducting comparisons. Because of this, an alternative measure of error variability (that is not influenced by violation of the sphericity assumption) will be presented later in this section.

At this point, employing MS_{res} as the error term, the following two **single degree of freedom comparisons** will be conducted: a) The **simple comparison** Condition 1 versus Condition 2, which is summarized in [Table 24.3](#); and b) The **complex comparison** Condition 3 versus the combined performance of Conditions 1 and 2, which is summarized in [Table 24.4](#).

Table 24.3 Planned Simple Comparison: Condition 1 Versus Condition 2

Condition	\bar{X}_j	Coefficient (c_j)	Product ($c_j)(\bar{X}_j)$	Squared Coefficient (c_j^2)
1	8.5	+1	(+1)(8.5) = +8.5	1
2	6.5	-1	(-1)(6.5) = -6.5	1
3	4.83	0	(0)(4.83) = 0	0
		$\Sigma c_j = 0$	$\Sigma(c_j)(\bar{X}_j) = 2$	$\Sigma c_j^2 = 2$

Since it will be assumed that the above comparisons are planned prior to collecting the data, **linear contrasts** will be conducted in which no attempt is made to control the value of the **familywise Type I error rate** (α_{FW}). The null hypothesis and nondirectional alternative hypothesis for the above comparisons are identical to those employed when the analogous comparisons are conducted in Section VI for the **single-factor between-subjects analysis variance** (i.e., $H_0: \mu_1 = \mu_2$ versus $H_1: \mu_1 \neq \mu_2$ for the simple comparison, and $H_0: \mu_3 = (\mu_1 + \mu_2)/2$ versus $H_1: \mu_3 \neq (\mu_1 + \mu_2)/2$ for the complex comparison).

Table 24.4 Planned Complex Comparison: Condition 3 Versus Conditions 1 and 2

Condition	\bar{X}_j	Coefficient (c_j)	Product ($c_j)(\bar{X}_j)$	Squared Coefficient (c_j^2)
1	8.5	$-\frac{1}{2}$	$\left(-\frac{1}{2}\right)(8.5) = -4.25$	$\frac{1}{4}$
2	6.5	$-\frac{1}{2}$	$\left(-\frac{1}{2}\right)(6.5) = -3.25$	$\frac{1}{4}$
3	4.83	+1	(+1)(4.83) = +4.83	1
		$\Sigma c_j = 0$	$\Sigma(c_j)(\bar{X}_j) = -2.67$	$\Sigma c_j^2 = 1.5$

Equations 21.17 and 21.18, which are employed to compute SS_{comp} and MS_{comp} for linear contrasts for the **single-factor between-subjects analysis of variance**, are also employed for linear contrasts for the **single-factor within-subjects analysis of variance**. The latter equations are employed below for the simple comparison Condition 1 versus Condition 2.

$$SS_{\text{comp}} = \frac{n[\Sigma(c_j)(\bar{X}_j)]^2}{\Sigma c_j^2} = \frac{6(2)^2}{2} = 12$$

$$MS_{\text{comp}} = \frac{SS_{\text{comp}}}{df_{\text{comp}}} = \frac{12}{1} = 12$$

Equation 24.16 (which is identical to Equation 21.19, except for the fact that it employs MS_{res} as the error term) is used to compute the value of F_{comp} .

$$F_{\text{comp}} = \frac{MS_{\text{comp}}}{MS_{\text{res}}} = \frac{12}{.49} = 24.49 \quad (\text{Equation 24.16})$$

The degrees of freedom employed in evaluating the obtained value $F_{\text{comp}} = 24.49$ are $df_{\text{num}} = df_{\text{comp}} = 1$ (since in a **single degree of freedom comparison** df_{comp} will always equal 1) and $df_{\text{den}} = df_{\text{res}} = 10$. For $df_{\text{num}} = 1$ and $df_{\text{den}} = 10$, the tabled critical .05 and .01 F values in **Table A10** are $F_{.05} = 4.96$ and $F_{.01} = 10.04$. Since the obtained value $F_{\text{comp}} = 24.49$ is greater than both of the aforementioned critical values, the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is supported at both the .05 and .01 levels.

Applying Equations 21.17, 21.18, and 24.16 to the complex comparison Condition 3 versus Conditions 1 and 2, the following result is obtained.

$$SS_{\text{comp}} = \frac{n \left[\sum (c_j)(\bar{X}_j) \right]^2}{\sum c_j^2} = \frac{6(-2.67)^2}{1.5} = 28.52$$

$$MS_{\text{comp}} = \frac{SS_{\text{comp}}}{df_{\text{comp}}} = \frac{28.52}{1} = 28.52$$

$$F_{\text{comp}} = \frac{MS_{\text{comp}}}{MS_{\text{res}}} = \frac{28.52}{.49} = 58.20$$

As is the case for the simple comparison, the degrees of freedom employed for the complex comparison in evaluating the value $F_{\text{comp}} = 58.20$ are $df_{\text{num}} = df_{\text{comp}} = 1$ and $df_{\text{den}} = df_{\text{res}} = 10$. Since the obtained value $F_{\text{comp}} = 58.20$ is greater than the tabled critical values $F_{.05} = 4.96$ and $F_{.01} = 10.04$, the nondirectional alternative hypothesis $H_1: \mu_3 \neq (\mu_1 + \mu_2)/2$ is supported at both the .05 and .01 levels.

For both of the comparisons that have been conducted, a CD value can be computed that identifies a minimum required difference in order for two means (or sets of means) to differ from one another at a prespecified level of significance. For both the simple comparison Condition 1 versus Condition 2 and the complex comparison Condition 3 versus Conditions 1 and 2, a CD value will be computed employing **multiple t tests/Fisher's LSD test** (which is equivalent to a **linear contrast** in which the value of α_{FW} is not controlled) and the **Scheffé test**. Whereas **multiple t tests/Fisher's LSD test** allow a researcher to determine the minimum CD value (designated CD_{LSD}) that can be computed through use of any of the comparison procedures that are described for the **single-factor between-subjects analysis of variance**, the **Scheffé test** generally results in the maximum CD value (designated CD_S) that can be computed by the available procedures. Thus, if at a prespecified level of significance the obtained difference for a comparison is equal to or greater than CD_S , it will be significant regardless of which comparison procedure is employed. On the other hand, if the obtained difference for a comparison is less than CD_{LSD} , it will not achieve significance, regardless of which comparison procedure is employed. In illustrating the computation of CD values for both simple and complex comparisons, it will be assumed that the total number of comparisons conducted is $c = 3$.¹⁰ It will also be assumed that when the researcher wants to control the value of the **familywise Type I error rate**, the value $\alpha_{FW} = .05$ is employed irrespective of which comparison procedure is used.

The equations employed for computing the values CD_{LSD} and CD_S are essentially the same as those used for the **single-factor between-subjects analysis of variance**. Equations 24.17 and 24.18 are employed below to compute the values of CD_{LSD} and CD_S for the simple comparison Condition 1 versus Condition 2. Note that Equations 24.17 and 24.18 are identical to Equations 21.24 and 21.32, except for the fact that MS_{res} is employed as the error term in both equations, and in Equation 24.18 df_{BC} is used in place of df_{BG} in determining the numerator degrees of

freedom. In employing Equation 24.18, the tabled critical value $F_{.05} = 4.10$ is employed since $df_{\text{num}} = df_{BC} = 2$ and $df_{\text{den}} = df_{\text{res}} = 10$.

$$CD_{LSD} = \sqrt{F_{(1, \text{res})}} \sqrt{\frac{2MS_{\text{res}}}{n}} = \sqrt{4.96} \sqrt{\frac{(2)(.49)}{6}} = .90 \quad (\text{Equation 24.17})$$

$$\begin{aligned} CD_S &= \sqrt{(k - 1)(F_{(df_{BC}, df_{\text{res}})})} \sqrt{\frac{2MS_{\text{res}}}{n}} \\ &= \sqrt{(3 - 1)(4.10)} \sqrt{\frac{(2)(.49)}{6}} = 1.16 \end{aligned} \quad (\text{Equation 24.18})$$

Thus, if one employs **multiple *t* tests/Fisher's LSD test** (i.e., conducts linear contrasts with α_{FW} not adjusted), in order to differ significantly at the .05 level, the means of any two conditions must differ from one another by at least .90 units. If, on the other hand, the **Scheffé test** is employed, in order to differ significantly the means of any two conditions must differ from one another by at least 1.16 units. Since the difference score for the comparison Condition 1 versus Condition 2 equals $\bar{X}_1 - \bar{X}_2 = 2$, the comparison is significant at the .05 level, regardless of which comparison procedure is employed.

Table 24.5 summarizes the differences between pairs of means involving all of the experimental conditions. Since the difference scores for all three simple/pairwise comparisons are greater than $CD_S = 1.16$, all of the comparisons are significant at the .05 level, regardless of which comparison procedure is employed.

Table 24.5 Differences Between Pairs of Means in Example 24.1

$\bar{X}_1 - \bar{X}_2 = 8.5 - 6.5 = 2$
$\bar{X}_1 - \bar{X}_3 = 8.5 - 4.83 = 3.67$
$\bar{X}_2 - \bar{X}_3 = 6.5 - 4.83 = 1.67$

The complex comparison Condition 3 versus Conditions 1 and 2 is illustrated below employing Equations 24.19 and 24.20. The latter two equations (which are the generic forms of Equations 24.17 and 24.18 that can be used for both simple and complex comparisons) are identical to Equations 21.25 and 21.33 (except for the use of MS_{res} as the error term, and the use of df_{BC} in place of df_{BG} in Equation 24.20).

$$\begin{aligned} CD_{LSD} &= \sqrt{F_{(1, \text{res})}} \sqrt{\frac{(\sum c_j^2)(MS_{\text{res}})}{n}} \\ &= \sqrt{4.96} \sqrt{\frac{(1.5)(.49)}{6}} = .78 \end{aligned} \quad (\text{Equation 24.19})$$

$$\begin{aligned} CD_S &= \sqrt{(k - 1)(F_{(df_{BC}, df_{\text{res}})})} \sqrt{\frac{(\sum c_j^2)(MS_{\text{res}})}{n}} \\ &= \sqrt{(3 - 1)(4.10)} \sqrt{\frac{(1.5)(.49)}{6}} = 1.00 \end{aligned} \quad (\text{Equation 24.20})$$

Thus, if one employs **multiple t tests/Fisher's LSD test** (i.e., conducts a linear contrast with α_{FW} not adjusted), in order to differ significantly the difference between \bar{X}_3 and $(\bar{X}_1 + \bar{X}_2)/2$ must be at least .78 units. If, on the other hand, the **Scheffé test** is employed, in order to differ significantly the two sets of means must differ from one another by at least 1.00 unit. Since the obtained difference of 2.67 is greater than $CD_S = 1.00$, the nondirectional alternative hypothesis $H_1: \mu_3 \neq (\mu_1 + \mu_2)/2$ is supported, regardless of which comparison procedure is employed.

The computation of a confidence interval for a comparison The procedure that is described for computing a confidence interval for a comparison for the **single-factor between-subjects analysis of variance** can also be used with the **single-factor within-subjects analysis of variance**. Thus, in the case of the latter analysis of variance, a confidence interval for a comparison is computed by adding to and subtracting the relevant CD value for the comparison from the obtained difference between the means involved in the comparison. As an example, let us assume the **Scheffé test** is employed to compute the value $CD_S = 1.16$ for the comparison Condition 1 versus Condition 2. To compute the 95% confidence interval, the value 1.16 is added to and subtracted from 2, which is the absolute value of the difference between the two means. Thus, $CI_{.95} = 2 \pm 1.16$, which can also be written as $.84 \leq (\mu_1 - \mu_2) \leq 3.16$. In other words, the researcher can be 95% confident (or the probability is .95) that the mean of the population represented by Condition 1 is between .84 and 3.16 units larger than the mean of the population represented by Condition 2.

Alternative methodology for computing MS_{res} for a comparison Earlier in this section it is noted that if the sphericity assumption underlying the **single-factor within-subjects analysis of variance** is violated, MS_{res} may not provide an accurate measure of error variability for a specific comparison. Because of this, many sources recommend that when the sphericity assumption is violated a separate measure of error variability be computed for each comparison that is conducted. The procedure that will be discussed in this section (which is described in Keppel (1991)) can be employed any time a researcher has reason to believe that MS_{res} employed in computing the omnibus F value is not representative of the actual error variability for the experimental conditions involved in a specific comparison. The procedure (which will be demonstrated for both a simple and complex comparison) requires that a **single-factor within-subjects analysis of variance** be conducted employing only the data for those experimental conditions involved in a comparison. In the case of a simple comparison, the scores of subjects in the two comparison conditions are evaluated with the analysis of variance. In the case of a complex comparison, a weighted score must be computed for each subject for any composite mean that is a combination of two or more experimental conditions.

With respect to a simple planned comparison, the procedure will be employed to evaluate the difference between Condition 1 and Condition 3. The reason it will not be used for the Condition 1 versus Condition 2 comparison is because the error variability associated with the latter comparison is $MS_{res} = 0$. The reason why $MS_{res} = 0$ for the latter comparison is revealed by inspection of the scores of the six subjects in [Table 24.1](#). Observe that the score of each of the six subjects in Condition 1 is two units higher than it is in Condition 2. Anytime all of the subjects in a within-subjects design involving two treatments obtain identical difference scores, the measure of error variability will equal zero. Consequently, whenever the value of $MS_{res} = 0$, the value of F_{comp} will be indeterminate, since the denominator of the F ratio will equal zero. In such an instance, one can either use the MS_{res} value employed in computing the omnibus F value, or elect to use the smallest MS_{res} value that can be computed for any of the other simple comparisons in the set of data.¹¹

Table 24.6 summarizes the data for the comparison Condition 1 versus Condition 3. Note that the values $\Sigma X_T = 80$ and $\Sigma X_T^2 = 606$ differ from those computed in Table 24.1, since in this instance they only include the data for two of the three experimental conditions.

Table 24.6 Data for Comparison of Condition 1 Versus Condition 3

	Condition 1		Condition 3		ΣS_i
	X_1	X_1^2	X_3	X_3^2	
Subject 1	9	81	4	16	13
Subject 2	10	100	7	49	17
Subject 3	7	49	3	9	10
Subject 4	10	100	7	49	17
Subject 5	7	49	2	4	9
Subject 6	8	64	6	36	14
$\Sigma X_1 = 51$		$\Sigma X_1^2 = 443$	$\Sigma X_2 = 29$	$\Sigma X_2^2 = 163$	$\Sigma X_T = 80$
$\Sigma X_T = 51 + 29 = 80$		$\Sigma X_T^2 = 443 + 163 = 606$			

The sum of squares values that are required for the analysis of variance are computed with Equations 24.2–24.5. Note that since we are only dealing with two conditions, $k = 2$, and thus, $N = nk = (6)(2) = 12$.

$$SS_T = \Sigma X_T^2 - \frac{(\Sigma X_T)^2}{N} = 606 - \frac{(80)^2}{12} = 72.67$$

$$SS_{BC} = \left[\frac{(\Sigma X_1)^2}{n} + \frac{(\Sigma X_3)^2}{n} \right] - \frac{(\Sigma X_T)^2}{N} = \left[\frac{(51)^2}{6} + \frac{(29)^2}{6} \right] - \frac{(80)^2}{12} = 40.34$$

$$SS_{BS} = \left[\frac{(\Sigma S_1)^2}{k} + \dots + \frac{(\Sigma S_6)^2}{k} \right] - \frac{(\Sigma X_T)^2}{N} = \left[\frac{(13)^2}{2} + \frac{(17)^2}{2} + \dots + \frac{(14)^2}{2} \right] - \frac{(80)^2}{12} = 28.67$$

$$SS_{\text{res}} = SS_T - SS_{BC} - SS_{BS} = 72.67 - 40.34 - 28.67 = 3.66$$

Upon computing the sum of squares values, the appropriate degrees of freedom (employing Equations 24.10–24.13) and mean square values (employing Equations 24.7–24.9) are computed. Employing Equation 24.15, the value $F = F_{\text{comp}} = 55.26$ is computed for the comparison. The analysis of variance is summarized in Table 24.7. Note that in computing the degrees of freedom for the analysis, the values $n = 6$ and $k = 2$ are employed.

Table 24.7 Summary Table for Analysis of Variance for Comparison of Condition 1 Versus Condition 3

Source of variation	<i>SS</i>	<i>df</i>	<i>MS</i>	<i>F</i>
Between-subjects	28.67	5	5.73	55.26
Between-conditions	40.34	1	40.34	
Residual	3.66	5	.73	
Total	72.67	11		

Employing $df_{\text{num}} = df_{BC} = df_{\text{comp}} = 1$ and $df_{\text{den}} = df_{\text{res}} = 5$, the tabled critical values employed in Table A10 are $F_{.05} = 6.61$ and $F_{.01} = 16.26$. Since the obtained value $F = 55.26$

is greater than both of the aforementioned critical values, the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_3$ is supported at both the .05 and .01 levels. The reader should note that the value $df_{\text{res}} = 5$ employed for the comparison of Condition 1 versus Condition 3 is less than the value $df_{\text{res}} = 10$ employed when the same comparison was conducted earlier in this section employing the value $MS_{\text{res}} = .49$ obtained for the omnibus F test. The lower df_{res} value associated with the method under discussion results in a less powerful test of the alternative hypothesis. In some instances the loss of power associated with this method may be offset if the value of MS_{res} for the comparison conditions is smaller than the value of MS_{res} obtained for the omnibus F test.

Employing Equations 24.17 and 24.18, a CD_{LSD} and CD_S value can be computed for the Condition 1 versus Condition 3 comparison.

$$CD_{LSD} = \sqrt{F_{(1, \text{res})}} \sqrt{\frac{2MS_{\text{res}}}{n}} = \sqrt{6.61} \sqrt{\frac{(2)(.73)}{6}} = 1.27$$

$$CD_S = \sqrt{(k-1)F_{(df_{BC}, df_{\text{res}})}} \sqrt{\frac{2MS_{\text{res}}}{n}} = \sqrt{(3-1)(4.10)} \sqrt{\frac{(2)(.73)}{6}} = 1.41$$

In computing $CD_{LSD} = 1.27$, the tabled critical F value employed in Equation 24.17 is based on $df_{\text{num}} = df_{BC} = df_{\text{comp}} = 1$, and $df_{\text{den}} = df_{\text{res}} = 5$. Note that $df_{\text{den}} = df_{\text{res}} = 5$ is only based on the data for the two experimental conditions employed in the comparison. In computing $CD_S = 1.41$, however, the tabled critical F value employed in Equation 24.18 is based on all three conditions employed in the experiment, and thus $df_{BC} = 2$ and $df_{\text{res}} = 10$. Note that the values $CD_{LSD} = 1.27$ and $CD_S = 1.41$ are larger than the corresponding values $CD_{LSD} = .90$ and $CD_S = 1.16$, which are computed for simple comparisons when $MS_{\text{res}} = .49$ is employed. It should be obvious through inspection of Equations 24.17 and 24.18, that the larger the value of MS_{res} , the greater the magnitude of the computed CD value.

At the beginning of this section it is noted that when a complex comparison is conducted employing a residual variability which is based only on the specific conditions involved in the comparison, a weighted score must be computed for each subject for any composite mean that is a combination of two or more experimental conditions. This will now be illustrated for the comparison of Condition 3 versus the combined performance of Conditions 1 and 2.

Table 24.8 Data for Comparison of Condition 3 Versus Conditions 1 and 2

	Condition 3		Conditions 1 & 2		ΣS_i
	X_3	X_3^2	$X_{1/2}$	$X_{1/2}^2$	
Subject 1	4	16	8	64	12
Subject 2	7	49	9	81	16
Subject 3	3	9	6	36	9
Subject 4	7	49	9	81	16
Subject 5	2	4	6	36	8
Subject 6	6	36	7	49	13
$\Sigma X_3 = 29$		$\Sigma X_3^2 = 163$	$\Sigma X_{1/2} = 45$	$\Sigma X_{1/2}^2 = 347$	$\Sigma X_T = 74$
$\Sigma X_T = 29 + 45 = 74$			$\Sigma X_T^2 = 163 + 347 = 510$		

Table 24.8 contains the scores of the six subjects in Condition 3 and a weighted score for each subject for Conditions 1 and 2. The weighted score of a subject for a combination of two or more conditions is obtained as follows: a) A subject's score in each condition is multiplied by

the absolute value of the coefficient for that condition (based on the coefficients for the comparison in Table 24.4); and b) The subject's weighted score is the sum of the products obtained in part a).

To clarify how the aforementioned procedure is employed to compute the weighted scores in Table 24.8, the computation of weighted scores for Subjects 1 and 2 will be described. Since the scores of Subject 1 in Conditions 1 and 2 are 9 and 7, each score is multiplied by the absolute value of the coefficient for the corresponding condition. Employing the absolute values of the coefficients noted in Table 24.4 for Conditions 1 and 2, each score is multiplied by 1/2, yielding $(9)(1/2) = 4.5$ and $(7)(1/2) = 3.5$. The weighted score for Subject 1 is obtained by summing the latter two values. Thus, the weighted score for Subject 1 is $4.5 + 3.5 = 8$. In the case of Subject 2, $(10)(1/2) = 5$ and $(8)(1/2) = 4$. Thus, the weighted score for Subject 2 is $5 + 4 = 9$. The same procedure is used for the remaining four subjects.¹²

The sum of squares values that are required for the analysis of variance are computed with Equations 24.2–24.5. Note that since we are only dealing with two sets of means, $k = 2$, and thus, $N = nk = (6)(2) = 12$.

$$SS_T = \sum X_T^2 - \frac{(\sum X_T)^2}{N} = 510 - \frac{(74)^2}{12} = 53.67$$

$$SS_{BC} = \left[\frac{(\sum X_3)^2}{n} + \frac{(\sum X_{1/2})^2}{n} \right] - \frac{(\sum X_T)^2}{N} = \left[\frac{(29)^2}{6} + \frac{(45)^2}{6} \right] - \frac{(74)^2}{12} = 21.34$$

$$SS_{BS} = \left[\frac{(\sum S_1)^2}{k} + \dots + \frac{(\sum S_6)^2}{k} \right] - \frac{(\sum X_T)^2}{N} = \left[\frac{(12)^2}{2} + \frac{(16)^2}{2} + \dots + \frac{(13)^2}{2} \right] - \frac{(74)^2}{12} = 28.67$$

$$SS_{res} = SS_T - SS_{BC} - SS_{BS} = 53.67 - 21.34 - 28.67 = 3.66$$

Upon computing the sum of squares values, the appropriate degrees of freedom (employing Equations 24.10–24.13) and mean square values (employing Equations 24.7–24.9) are computed. Employing Equation 24.15, the value $F = F_{comp} = 29.23$ is computed for the comparison. The analysis of variance is summarized in Table 24.9. Note that in computing the degrees of freedom for the analysis, the values $n = 6$ and $k = 2$ are employed.

**Table 24.9 Summary Table for Analysis of Variance
for Comparison of Condition 3 Versus Conditions 1 and 2**

Source of variation	SS	df	MS	F
Between-subjects	28.67	5	5.73	
Between-conditions	21.34	1	21.34	29.23
Residual	3.66	5	.73	
Total	53.67	11		

Employing $df_{num} = df_{BC} = df_{comp} = 1$ and $df_{den} = df_{res} = 5$, the tabled critical values employed in Table A10 are $F_{.05} = 6.61$ and $F_{.01} = 16.26$. Since the obtained value $F = 29.23$ is greater than both of the aforementioned tabled critical values, the nondirectional alternative hypothesis $H_1: \mu_3 \neq (\mu_1 + \mu_2)/2$ is supported at both the .05 and .01 levels.

Employing Equations 24.19 and 24.20, a CD_{LSD} and CD_s value can be computed for the complex comparison.

$$\begin{aligned}
 CD_{LSD} &= \sqrt{F_{(1, \text{res})}} \sqrt{\frac{(\sum c_j^2)(MS_{\text{res}})}{n}} = \sqrt{6.61} \sqrt{\frac{(1.5)(.73)}{6}} = 1.10 \\
 CD_S &= \sqrt{(k-1)(F_{(df_{BC}, df_{\text{res}})})} \sqrt{\frac{(\sum c_j^2)(MS_{\text{res}})}{n}} \\
 &= \sqrt{(3-1)(4.10)} \sqrt{\frac{(1.5)(.73)}{6}} = 1.22
 \end{aligned}$$

Note that the values $CD_{LSD} = 1.10$ and $CD_S = 1.22$ are larger than the corresponding values $CD_{LSD} = .78$ and $CD_S = 1.00$, which are computed for the same complex comparison when $MS_{\text{res}} = .49$ is used.

2. Comparing the means of three or more conditions when $k \geq 4$ Within the framework of a **single-factor within-subjects analysis of variance** involving $k = 4$ or more conditions, a researcher may wish to evaluate a general hypothesis with respect to the means of a subset of conditions, where the number of conditions in the subset is some value less than k . Although the latter type of situation is not commonly encountered in research, this section will describe the protocol for conducting such an analysis. Specifically, the protocol described for the analogous analysis for a **single-factor between-subjects analysis of variance** will be extended to the **single-factor within-subjects analysis of variance**.

To illustrate, assume that a fourth experimental condition is added to Example 24.1. Assume that the scores of Subjects 1–6 in Condition 4 are respectively: 3, 8, 2, 6, 4, 6. Thus, $\sum X_4 = 29$, $\bar{X}_4 = 4.83$, and $\sum X_4^2 = 165$. If the data for Condition 4 are integrated into the data for the other three conditions (which are summarized in Table 24.1), the following summary values are computed: $N = nk = (6)(4) = 24$, $\sum X_T = 148$, $\sum X_T^2 = 1034$. Substituting the revised values for $k = 4$ conditions in Equations 24.2–24.5, the following sum of squares values are computed: $SS_T = 121.33$, $SS_{BC} = 54.66$, $SS_{BS} = 54.33$, $SS_{\text{res}} = 12.34$. Employing the values $k = 4$ and $n = 6$ in Equations 24.10–24.12, the values $df_{BC} = 4 - 1 = 3$, $df_{BS} = 6 - 1 = 5$, and $df_{\text{res}} = (6 - 1)(4 - 1) = 15$ are computed. Substituting the appropriate values for the sums of squares and degrees of freedom in Equations 24.7–24.9, the values $MS_{BC} = 54.66/3 = 18.22$, $MS_{BS} = 54.33/5 = 10.87$, and $MS_{\text{res}} = 12.34/15 = .82$ are computed. Equation 24.15 is employed to compute the value $F = 18.22/.82 = 22.22$. Table 24.10 is the summary table of the analysis of variance.

**Table 24.10 Summary Table of Analysis of Variance
for Example 24.1 When $k = 4$**

Source of variation	<i>SS</i>	<i>df</i>	<i>MS</i>	<i>F</i>
Between-subjects	54.33	5	10.87	
Between-conditions	54.66	3	18.22	22.22
Residual	12.34	15	.82	
	121.33	23		

Employing $df_{\text{num}} = 3$ and $df_{\text{den}} = 15$, the tabled critical .05 and .01 F values are $F_{.05} = 3.29$ and $F_{.01} = 5.42$. Since the obtained value $F = 22.22$ is greater than both of the aforementioned critical values, the null hypothesis (which for $k = 4$ is $H_0: \mu_1 = \mu_2 = \mu_3 = \mu_4$) can be rejected at both the .05 and .01 levels.

Let us assume that prior to the above analysis the researcher has reason to believe that Conditions 1, 2, and 3 may be distinct from Condition 4. However, before he contrasts the composite mean of Conditions 1, 2, and 3 with the mean of Condition 4 (i.e., conducts the complex comparison which evaluates the null hypothesis $H_0: (\mu_1 + \mu_2 + \mu_3)/3 = \mu_4$), he decides to evaluate the null hypothesis $H_0: \mu_1 = \mu_2 = \mu_3$. If the latter null hypothesis is retained, he will assume that the three conditions share a common mean value, and on the basis of this he will compare their composite mean with the mean of Condition 4. In order to evaluate the null hypothesis $H_0: \mu_1 = \mu_2 = \mu_3$, it is necessary for the researcher to conduct a separate analysis of variance that just involves the data for the three conditions identified in the null hypothesis. The latter analysis of variance has already been conducted, since it is the original analysis of variance that is employed for Example 24.1 — the results of which are summarized in Table 24.2.

Upon conducting an analysis of variance on the data for all $k = 4$ conditions as well as an analysis of variance on the data for the subset comprised of $k_{\text{subset}} = 3$ conditions, the researcher has the necessary information to compute the appropriate F ratio (which will be represented with the notation $F_{(1/2/3)}$) for evaluating the null hypothesis $H_0: \mu_1 = \mu_2 = \mu_3$. If we apply the same logic employed when the analogous analysis is conducted in reference to the **single-factor between-subjects analysis of variance**, the following values are employed to compute the F ratio to evaluate the latter null hypothesis: a) $MS_{BC} = 20.23$ (which is the value of MS_{BC} computed for the analysis of variance in Table 24.2 that involves only the three conditions identified in the null hypothesis $H_0: \mu_1 = \mu_2 = \mu_3$) is employed as the numerator of the F ratio; and b) $MS_{\text{res}} = .82$ (which is the value of MS_{res} computed in Table 24.10 for the omnibus F test when the data for all $k = 4$ conditions are evaluated) is employed as the denominator of the F ratio. The use of $MS_{\text{res}} = .82$ instead of $MS_{\text{res}} = .49$ (which is the value of MS_{res} computed for the analysis of variance in Table 24.2) as the denominator of the F ratio is predicated on the assumption that $MS_{\text{res}} = .82$ provides a more accurate estimate of error variability than $MS_{\text{res}} = .49$. If the latter assumption is made, the value $F_{(1/2/3)} = 24.67$ is computed.

$$F_{(1/2/3)} = \frac{MS_{BC(1/2/3)}}{MS_{\text{res}(1/2/3/4)}} = \frac{20.23}{.82} = 24.67$$

The degrees of freedom employed for the analysis are based on the mean square values employed in computing the $F_{(1/2/3)}$ ratio. Thus: $df_{\text{num}} = k_{\text{subset}} - 1 = 3 - 1 = 2$ (where $k_{\text{subset}} = 3$ conditions) and $df_{\text{den}} = df_{\text{res}(1/2/3/4)} = 15$ (which is df_{res} for the omnibus F test involving all $k = 4$ conditions). For $df_{\text{num}} = 2$ and $df_{\text{den}} = 15$, $F_{.05} = 3.68$ and $F_{.01} = 6.36$. Since the obtained value $F = 24.67$ is greater than both of the aforementioned critical values, the null hypothesis can be rejected at both the .05 and .01 levels. Thus, the data do not support the researcher's hypothesis that Conditions 1, 2, and 3 represent a homogeneous subset. In view of this, the researcher would not conduct the contrast $(X_1 + X_2 + X_3)/3$ versus X_4 .

If a researcher is not willing to assume that $MS_{\text{res}} = .82$ provides a more accurate estimate of error variability than $MS_{\text{res}} = .49$, the latter value can be employed as the denominator term in computing the $F_{(1/2/3)}$ ratio. Thus, if for some reason a researcher believes that by virtue of adding a fourth experimental condition experimental error is either increased or decreased, one can justify employing the value $MS_{\text{res}} = .49$ (computed for the $k = 3$ conditions) as the denominator term in computing the value $F_{(1/2/3)}$. If $MS_{\text{res}} = .49$ is employed to compute the F ratio, the value $F_{(1/2/3)} = 20.23/.49 = 41.29$ is computed. Since the latter value is greater than $F_{.05} = 3.68$ and $F_{.01} = 6.36$, the researcher can still reject the null hypothesis at both the .05 and .01 levels. However, the fact that $F_{(1/2/3)} = 41.29$ is substantially larger than $F_{(1/2/3)} = 24.67$

illustrates that depending upon which of the two error terms is employed, it is possible that they may lead to different conclusions regarding the status of the null hypothesis. The determination of which error term to use will be based on the assumptions a researcher is willing to make concerning the data. In the final analysis, in instances where the two error terms yield inconsistent results, it may be necessary for a researcher to conduct one or more replication studies in order to clarify the status of a null hypothesis.

3. Evaluation of the sphericity assumption underlying the single-factor within-subjects analysis of variance In Section I it is noted that one of the assumptions underlying the **single-factor within-subjects analysis of variance** is the existence of a condition referred to as **sphericity**. Sphericity exists when there is homogeneity of variance among the populations of difference scores. The latter can be explained as follows: Assume that for each of the n subjects who serve under all k experimental conditions, a difference score is calculated for all pairs of conditions. The number of difference scores that can be computed for each subject will equal $[k(k-1)]/2$. When $k=3$, three sets of difference scores can be computed. Specifically: a) A set of difference scores that is the result of subtracting each subject's score in Condition 2 from the subject's score in Condition 1; b) A set of difference scores that is the result of subtracting each subject's score in Condition 3 from the subject's score in Condition 1; and c) A set of difference scores that is the result of subtracting each subject's score in Condition 3 from the subject's score in Condition 2.¹³

The sphericity assumption states that if the estimated population variances for the three sets of difference scores are computed, the values of the variances should be equal. The derivation of the three sets of difference scores for Example 24.1, and the computation of their estimated population variances are summarized in Table 24.11. Note that for each set of difference scores, a D value is computed for each subject. The estimated population variance of the D values (which is computed with Equation I.5) represents the estimated population variance of a set of difference scores.

Visual inspection of the estimated population variances of the difference scores reveals that the three variances are quite close to one another. This latter fact suggests that the sphericity assumption is unlikely to have been violated. Unfortunately, the tests that are discussed in this book for evaluating homogeneity of variance are not appropriate for comparing the variances of the difference scores within the framework of evaluating the sphericity assumption. The procedures that have been developed for evaluating sphericity require the use of matrix algebra and are generally conducted with the aid of a computer. Further reference to such procedures will be made later in this discussion.

Sources on analysis of variance (e.g., Myers and Well (1991, 1995)) note that there is another condition known as **compound symmetry** which is sufficient, although not necessary, in order for sphericity to exist. Compound symmetry, which represents a special case of sphericity, exists when both of the following conditions have been met: a) **Homogeneity of variance** — All of the populations that are represented by the k experimental conditions have equal variances; and b) **Homogeneity of covariance** — All of the population covariances are equal to one another.

At this point we will examine the variances of the three experimental conditions, as well as the **covariances** of each pair of conditions. Employing Equation I.5, the estimated population variance for each of the three experimental conditions is computed.

$$\hat{s}_1^2 = \frac{\sum X_1^2 - \frac{(\sum X_1)^2}{n}}{n - 1} = \frac{443 - \frac{(51)^2}{6}}{5} = 1.9$$

$$\hat{s}_2^2 = \frac{\Sigma X_2^2 - \frac{(\Sigma X_2)^2}{n}}{n - 1} = \frac{263 - \frac{(39)^2}{6}}{5} = 1.9$$

$$\hat{s}_3^2 = \frac{\Sigma X_3^2 - \frac{(\Sigma X_3)^2}{n}}{n - 1} = \frac{163 - \frac{(29)^2}{6}}{5} = 4.57$$

Table 24.11 Computation of Estimated Population Variances of Difference Scores

Condition 1 versus Condition 2				
	X_1	X_2	D	D^2
Subject 1	9	7	2	4
Subject 2	10	8	2	4
Subject 3	7	5	2	4
Subject 4	10	8	2	4
Subject 5	7	5	2	4
Subject 6	8	6	2	4
			$\Sigma D = 12$	$\Sigma D^2 = 24$
$\hat{s}_{(X_1 - X_2)}^2 = \frac{\Sigma D^2 - \frac{(\Sigma D)^2}{n}}{n - 1} = \frac{24 - \frac{(12)^2}{6}}{6 - 1} = 0$				
Condition 1 versus Condition 3				
	X_1	X_3	D	D^2
Subject 1	9	4	5	25
Subject 2	10	7	3	9
Subject 3	7	3	4	16
Subject 4	10	7	3	9
Subject 5	7	2	5	25
Subject 6	8	6	2	4
			$\Sigma D = 22$	$\Sigma D^2 = 88$
$\hat{s}_{(X_1 - X_3)}^2 = \frac{\Sigma D^2 - \frac{(\Sigma D)^2}{n}}{n - 1} = \frac{88 - \frac{(22)^2}{6}}{6 - 1} = 1.47$				
Condition 2 versus Condition 3				
	X_2	X_3	D	D^2
Subject 1	7	4	3	9
Subject 2	8	7	1	1
Subject 3	5	3	2	4
Subject 4	8	7	1	1
Subject 5	5	2	3	9
Subject 6	6	6	0	0
			$\Sigma D = 10$	$\Sigma D^2 = 24$
$\hat{s}_{(X_2 - X_3)}^2 = \frac{\Sigma D^2 - \frac{(\Sigma D)^2}{n}}{n - 1} = \frac{24 - \frac{(10)^2}{6}}{6 - 1} = 1.47$				

Although Equation 17.9 is not actually employed to evaluate homogeneity of variance within the framework of the sphericity assumption, for illustrative purposes it will be used. The latter equation is employed to evaluate the homogeneity of variance assumption for the ***t* test for two dependent samples** by contrasting the highest estimated population variance (which in Example 24.1 is $\hat{s}_3^2 = 4.57$) and the lowest estimated population variance (which in Example 24.1 is $\hat{s}_1^2 = \hat{s}_2^2 = 1.9$). In order to employ Equation 17.9 it is necessary to compute the correlation between subjects' scores in Condition 1 (which will be used to represent the lowest variance) and Condition 3. The value of the correlation coefficient is computed with Equation 17.7. Employing Equation 17.7, the value $r_{X_1 X_3} = .85$ is computed.¹⁴

$$r_{X_1 X_3} = \frac{\Sigma X_1 X_3 - \frac{(\Sigma X_1)(\Sigma X_3)}{n}}{\sqrt{\left[\Sigma X_1^2 - \frac{(\Sigma X_1)^2}{n}\right]\left[\Sigma X_3^2 - \frac{(\Sigma X_3)^2}{n}\right]}} = \frac{259 - \frac{(51)(29)}{6}}{\sqrt{\left[443 - \frac{(51)^2}{6}\right]\left[163 - \frac{(29)^2}{6}\right]}} = .85$$

Substituting the appropriate values in Equation 17.9, the value $t = 1.72$ is computed.

$$t = \frac{(\hat{s}_L^2 - \hat{s}_S^2)\sqrt{n-2}}{\sqrt{4\hat{s}_L^2\hat{s}_S^2(1 - r_{X_1 X_3}^2)}} = \frac{(4.57 - 1.9)\sqrt{6-2}}{\sqrt{(4)(4.57)(1.9)(1 - (.85)^2)}} = 1.72$$

The degrees of freedom associated with the t value computed with Equation 17.9 are $df = n - 2 = 4$. Since the computed value $t = 1.72$ is less than the tabled critical two-tailed value $t_{.05} = 2.78$ (for $df = 4$), the null hypothesis $H_0: \sigma_L^2 = \sigma_S^2$ (which states there is homogeneity of variance) is retained. Thus, there is no evidence to suggest that the homogeneity of variance assumption is violated.

Earlier in the discussion it was noted that the sphericity assumption assumes equal population covariances. Whereas variance is a measure of variability of the scores of n subjects on a single variable, covariance (which is discussed in more detail in Section VII of the **Pearson product-moment correlation coefficient (Test 28)**) is a measure that represents the degree to which two variables vary together. A positive covariance is associated with variables that are positively correlated with one another, and a negative covariance is associated with variables that are negatively correlated with one another.

Equation 24.21 is the general equation for computing **covariance**. The value computed with Equation 24.21 represents the estimated covariance between **Population a** and **Population b**.

$$\text{cov}_{X_a X_b} = \frac{\Sigma X_a X_b - \frac{(\Sigma X_a)(\Sigma X_b)}{n}}{n - 1} \quad (\text{Equation 24.21})$$

Since a covariance can be computed for any pair of experimental conditions, in Example 24.1 three covariances can be computed — specifically, the covariance between Conditions 1 and 2, the covariance between Conditions 1 and 3, and the covariance between Conditions 2 and 3. To illustrate the computation of the covariance, the covariance between Conditions 1 and 2 ($\text{cov}_{X_1 X_2}$) will be computed employing Equation 24.21. [Table 24.12](#), which reproduces the data for Conditions 1 and 2, summarizes the values employed in the calculation of the covariance.

Table 24.12 Data Required for Computing Covariance of Condition 1 and Condition 2

	X_1	X_2	$X_1 X_2$
Subject 1	9	7	63
Subject 2	10	8	80
Subject 3	7	5	35
Subject 4	10	8	80
Subject 5	7	5	35
Subject 6	8	6	48
	$\Sigma X_1 = 51$	$\Sigma X_2 = 39$	$\Sigma X_1 X_2 = 341$

Employing Equation 24.21 the value $\text{cov}_{X_1 X_2} = 1.9$ is computed.

$$\text{cov}_{X_1 X_2} = \frac{341 - \frac{(51)(39)}{6}}{6 - 1} = 1.9$$

If the relevant data for the other two sets of scores are employed, the values $\text{cov}_{X_1 X_3} = 2.5$ and $\text{cov}_{X_2 X_3} = 2.5$ are computed.

$$\text{cov}_{X_1 X_3} = \frac{259 - \frac{(51)(29)}{6}}{6 - 1} = 2.5$$

$$\text{cov}_{X_2 X_3} = \frac{201 - \frac{(39)(29)}{6}}{6 - 1} = 2.5$$

Since the three values for covariance are extremely close to one another, on the basis of visual inspection it would appear that the data are characterized by homogeneity of covariance. Coupled with the fact that homogeneity of variance also appears to exist, it would seem reasonable to conclude that the assumptions underlying compound symmetry (and thus of sphericity) are unlikely to have been violated.

The conditions necessary for compound symmetry (which, as previously noted, is not required in order for sphericity to exist), are, in fact, more stringent than the general requirement of sphericity (i.e., that there be homogeneity of variance among the populations of difference scores). Whenever data are characterized by compound symmetry, homogeneity of variance will exist among the populations of difference scores. However, it is possible to have homogeneity of variance among the populations of difference scores, yet not have compound symmetry.

A full discussion of the tests that are employed to evaluate the sphericity assumption underlying the **single-factor within-subjects analysis of variance** is beyond the scope of this book. The interested reader can find a description of such tests in selected texts that specialize in analysis of variance (e.g., Kirk (1982, 1995)). Keppel (1991) among others, notes, however, that tests which have been developed to evaluate the sphericity assumption have their own assumptions, and when the assumptions of the latter tests are violated (which may be more often than not), their reliability will be compromised. In view of this, Keppel (1991) questions the wisdom of employing such tests for evaluating the sphericity assumption.

At this point some general comments are in order regarding the consequences of violating the sphericity assumption. In the discussion of the ***t* test for two dependent samples** it is noted

that the latter test is much more sensitive to violation of the homogeneity of variance assumption than is the ***t* test for two independent samples (Test 11)**. Since this observation can be generalized to designs involving more than two treatments, the **single-factor within-subjects analysis of variance** is more sensitive to violation of the sphericity assumption than is the **single-factor between-subjects analysis of variance** to violation of its assumption of homogeneity of variance. In point of fact, most sources suggest that the **single-factor within-subjects analysis of variance** is extremely sensitive to violations of the sphericity assumption, and that when the latter assumption is violated, the tabled critical values in **Table A10** will not be accurate. Specifically, when the sphericity assumption is violated, the tabled critical *F* value associated with the appropriate degrees of freedom for the analysis of variance will be too low (i.e., the Type I error rate for the analysis will actually be higher than the prespecified value). One option proposed by Geisser and Greenhouse (1958) is to employ the tabled critical *F* value associated with $df_{\text{num}} = 1$ and $df_{\text{den}} = n - 1$ instead of the tabled critical *F* value associated with the usual degrees of freedom values (i.e., $df_{\text{num}} = df_{BC} = k - 1$ and $df_{\text{den}} = df_{\text{res}} = (n - 1)(k - 1)$). However, since the Geisser–Greenhouse method tends to overcorrect the value of *F* (i.e., it results in too high a critical value), some sources recommend an alternative but computationally more involved method developed by Box (1954) which does not result in as severe an adjustment of the critical *F* value as the Geisser–Greenhouse method.

Keppel (1991) notes that it is quite common for the sphericity assumption to be violated in experiments that utilize a within-subjects design. In view of this he recommends that in employing the **single-factor within-subjects analysis of variance** to evaluate the latter design, it is probably always prudent to run a more conservative test in order to insure that the Type I error rate is adequately controlled. An even more extreme viewpoint is articulated by other sources who recommend that when there is reason to believe that the sphericity assumption is violated, one should evaluate the data with a procedure other than the **single-factor within-subjects analysis of variance**. Specifically, these sources (e.g., Maxwell and Delaney (1990) and Howell (1992, 1997)) recommend evaluating the data for a within-subjects design with a **multivariate analysis of variance (MANOVA)** (described in Section VII of the **single-factor between-subjects analysis of variance**).

It should be apparent from the discussion in this section that there is lack of agreement with respect to the most appropriate methodology for dealing with violation of the sphericity assumption. A cynic might conclude that regardless of which method one employs, there will always be reason to doubt the accuracy of the probability value associated with the outcome of a study. As noted throughout this book, in situations where there are doubts concerning the reliability of an analysis, the most powerful tool the researcher has at her disposal is replication. In the final analysis, the truth regarding a hypothesis will ultimately emerge if one or more researchers conduct multiple studies that evaluate the same hypothesis. In instances where replication studies have been conducted, **meta-analysis** (discussed in Section IX (the **Addendum**) of the **Pearson product-moment correlation coefficient**) can be employed to derive a pooled probability value for all of the published studies.¹⁵

4. Computation of the power of the single-factor within-subjects analysis of variance Prior to reading this section the reader should review the discussion of power in Section VI of the **single-factor between-subjects analysis of variance**, since basically the same procedure is employed to determine the power of the **single-factor within-subjects analysis of variance**. The power of the **single-factor within-subjects analysis of variance** is computed with Equation 24.22, which is identical to Equation 21.38 (which is the equation used for computing the power of the **single-factor between-subjects analysis of variance**), except for the fact that the

estimated value of σ_{res}^2 is employed as the measure of error variability in place of σ_{WG}^2 (McFatter and Gollob (1986)).

$$\phi = \sqrt{n \left[\frac{\sum (\mu_j - \mu_T)^2}{k \sigma_{\text{res}}^2} \right]} \quad (\text{Equation 24.22})$$

Where: μ_j = The estimated mean of the population represented by Condition j
 μ_T = The grand mean, which is the average of the k estimated population means
 σ_{res}^2 = The estimated measure of error variability
 n = The number of subjects
 k = The number of experimental conditions

To illustrate the use of Equation 24.22 with Example 24.1, let us assume that prior to conducting the study the researcher estimates that the means of the populations represented by the three conditions are as follows: $\mu_1 = 8$, $\mu_2 = 6$, $\mu_3 = 4$. Additionally, it will be assumed that he estimates the population error variance associated with the analysis will equal $\sigma_{\text{res}}^2 = 1$. Based on this information, the value μ_T can be computed: $\mu_T = (\mu_1 + \mu_2 + \mu_3)/k = (8 + 6 + 4)/3 = 6$. The appropriate values are now substituted in Equation 24.22.

$$\phi = \sqrt{n \left[\frac{(8 - 6)^2 + (6 - 6)^2 + (4 - 6)^2}{(3)(1)} \right]} = \sqrt{2.67n} = 1.63\sqrt{n}$$

At this point **Table A15 (Graphs of the Power Function for the Analysis of Variance)** in the **Appendix** can be employed to determine the necessary sample size required in order to have the power stipulated by the experimenter. For our analysis (for which it will be assumed $\alpha = .05$) the appropriate set of curves to employ is the set for $df_{\text{num}} = df_{\text{BC}} = 2$. Let us assume we want the omnibus F test to have a power of at least .80. We now substitute what we consider to be a reasonable value for n in the equation $\phi = 1.63\sqrt{n}$ (which is the result obtained with Equation 24.22). To illustrate, the value $n = 6$ (the sample size employed in Example 24.1) is substituted in the equation. The resulting value is $\phi = 1.63\sqrt{6} = 3.99$.

The value $\phi = 3.99$ is located on the abscissa (X -axis) of the relevant set of curves in **Table A15** — specifically, the set for $df_{\text{num}} = 2$. At the point corresponding to $\phi = 3.99$, a perpendicular line is erected from the abscissa which intersects with the power curve that corresponds to $df_{\text{den}} = df_{\text{res}}$ employed for the omnibus F test. Since $df_{\text{res}} = 10$, the curve for the latter value is employed (or closest to it if a curve for the exact value is not available). At the point the perpendicular intersects the curve $df_{\text{res}} = 10$, a second perpendicular line is drawn in relation to the ordinate (Y -axis). The point at which this perpendicular intersects the ordinate indicates the power of the test. Since $\phi = 3.99$, we determine the power equals 1.¹⁶ Thus, if we employ six subjects in a within-subjects design, there is a 100% likelihood (which corresponds to a probability of 1) of detecting an effect size equal to or larger than the one stipulated by the researcher (which is a function of the estimated values for the population means relative to the value estimated for error variability). Since the probability of committing a Type II error is $\beta = 1 - \text{power}$, $\beta = 1 - 1 = 0$. This value represents the likelihood of not detecting an effect size equal to or greater than the one stipulated.

Equation 24.23 (described in McFatter and Gollob (1986)) can be employed to conduct a power analysis for a comparison associated with a **single-factor within-subjects analysis of variance**. Equation 24.23 is identical to Equation 21.39 (which is the equation for evaluating the

power of a comparison for the **single-factor between-subjects analysis of variance**), except for the fact that σ_{res}^2 is employed as the measure of error variability in place of σ_{WG}^2 .

$$\phi_{\text{comp}} = \sqrt{n \left[\frac{(\mu_a - \mu_b)^2}{2(\sigma_{\text{res}}^2)(\sum c_j^2)} \right]} \quad (\text{Equation 24.23})$$

As is the case for a **single-factor between-subjects analysis of variance**, Equation 24.23 can be used for both simple and complex single degree of freedom comparisons. As a general rule, the equation is used for planned comparisons. As noted in the discussion of the **single-factor between-subjects analysis of variance**, although the equation can be extended to unplanned comparisons, published power tables for the analysis of variance generally only apply to per comparison error rates of $\alpha = .05$ and $\alpha = .01$. In the case of planned and especially unplanned comparisons which involve α_{PC} rates other than .05 or .01, more detailed tables are required.

For single degree of freedom comparisons, the power curves in **Table A15** for $df_{\text{num}} = 1$ are always employed. The use of Equation 24.23 will be illustrated for the simple comparison Condition 1 versus Condition 2 (summarized in **Table 24.3**). Since $\sum c_j = 2$, and we have estimated $\mu_a = \mu_1 = 8$, $\mu_b = \mu_2 = 6$ and $\sigma_{\text{res}}^2 = 1$, the following result is obtained:

$$\phi_{\text{comp}} = \sqrt{n \left[\frac{(8 - 6)^2}{(2)(1)(2)} \right]} = \sqrt{n}$$

Substituting $n = 6$ in the equation $\phi_{\text{comp}} = \sqrt{n}$, we obtain $\phi_{\text{comp}} = \sqrt{6} = 2.45$. Employing the power curves for $df_{\text{num}} = 1$ with $\alpha = .05$, we use the curve for $df_{\text{res}} = 10$ (df_{res} employed for the omnibus F test) and determine that, when $\phi_{\text{comp}} = 2.45$, the power of the test is approximately .88.

5. Measures of magnitude of treatment effect for the single-factor within-subjects analysis of variance: Omega squared (Test 24g) and Cohen's f index (Test 24h) Prior to reading this section the reader should review the discussion of measures of magnitude of treatment effect in Section VI of both the **t test for two independent samples** and the **single-factor between-subjects analysis of variance**. The discussion for the latter test notes that the computation of an omnibus F value only provides a researcher with information regarding whether the null hypothesis can be rejected — i.e., whether a significant difference exists between at least two of the experimental conditions. The F value (as well as the level of significance with which it is associated), however, does not provide the researcher with any information regarding the size of any treatment effect that is present. As is noted in earlier discussions of treatment effect, the latter is defined as the proportion of the variability on the dependent variable that is associated with the independent variable/experimental conditions. The measures described in this section are variously referred to as **measures of effect size**, **measures of magnitude of treatment effect**, **measures of association**, and **correlation coefficients**.

Omega squared (Test 24g) The **omega squared** statistic is a commonly computed measure of treatment effect for the **single-factor within-subjects analysis of variance**. Keppel (1991) and Kirk (1995) note that there is disagreement with respect to which variance components should be employed in computing **omega squared** for a within-subjects design. One method of computing **omega squared** (which computes a value referred to as **standard omega squared**) was

employed in the previous edition of this book. The latter method expresses treatment (i.e., between-conditions) variability as a proportion of the sum of all the elements that account for variability in a within-subjects design. Equation 24.25, which is presented in Myers and Well (1995), can be employed to compute **standard omega squared**. (ω_s^2).¹⁷ The **omega squared** value computed with Equation 24.25 is an estimate of the proportion of variability in the data that is attributed to the experimental treatments (σ_{BC}^2) divided by the sum total of variability in the data (i.e., treatment variability (σ_{BC}^2) plus between-subjects variability (σ_{BS}^2) plus residual variability (σ_{res}^2)). Thus, Equation 24.24 represents the population parameter (ω_s^2) estimated by Equation 24.25. Employing Equation 24.25 with the data for Example 24.1, the value $\omega_s^2 = .44$ is computed.

$$\omega_s^2 = \frac{\sigma_{BC}^2}{\sigma_{BC}^2 + \sigma_{BS}^2 + \sigma_{res}^2} \quad \text{(Equation 24.24)}$$

$$\tilde{\omega}_s^2 = \frac{(k - 1)(MS_{BC} - MS_{res})}{(k - 1)(n - 1)MS_{res} + (k - 1)MS_{BC} + nMS_{BS}} \quad \text{(Equation 24.25)}$$

$$\tilde{\omega}_s^2 = \frac{(3 - 1)(20.23 - .49)}{(3 - 1)(6 - 1)(.49) + (3 - 1)(20.23) + (6)(7.39)} = .44$$

The value $\tilde{\omega}_s^2 = .44$ indicates that 44% (or a proportion of .44) of the variability on the dependent variable (the number of nonsense syllables correctly recalled) is associated with variability on the levels of the independent variable (noise).

A second method for computing **omega squared** computes what is referred to as **partial omega squared**. The latter measure, which Keppel (1991) and Kirk (1995) view as more meaningful than **standard omega squared**, ignores between-subjects variability, and expresses treatment (i.e., between-conditions) variability as a proportion of the sum of between-conditions and residual variability. Equation 24.27 is employed to compute **partial omega squared** (ω_p^2). Equation 24.26 represents the population parameter (ω_p^2) estimated by Equation 24.27. Employing Equation 24.27, the value $\tilde{\omega}_p^2 = .82$ is computed.

$$\omega_p^2 = \frac{\sigma_{BC}^2}{\sigma_{BC}^2 + \sigma_{res}^2} \quad \text{(Equation 24.26)}$$

$$\tilde{\omega}_p^2 = \frac{\tilde{\sigma}_{BC}^2}{\tilde{\sigma}_{BC}^2 + \tilde{\sigma}_{res}^2} \quad \text{(Equation 24.27)}$$

Where:

$$\tilde{\sigma}_{BC}^2 = \frac{df_{BC}(MS_{BC} - MS_{res})}{nk} = \frac{(2)(20.23 - .49)}{(6)(3)} = 2.19$$

$$\tilde{\sigma}_{res}^2 = MS_{res} = .49$$

$$\text{Thus: } \tilde{\omega}_p^2 = \frac{\tilde{\sigma}_{BC}^2}{\tilde{\sigma}_{BC}^2 + \tilde{\sigma}_{res}^2} = \frac{2.19}{2.19 + .49} = .82$$

Equation 24.28 can also be employed to compute the value of **partial omega squared**.

$$\begin{aligned}\tilde{\omega}_p^2 &= \frac{(k - 1)(F - 1)}{(k - 1)(F - 1) + nk} \\ \tilde{\omega}_p^2 &= \frac{(3 - 1)(41.29 - 1)}{(3 - 1)(41.29 - 1) + (6)(3)} = .82\end{aligned}\quad (\text{Equation 24.28})$$

The value $\tilde{\omega}_p^2 = .82$ computed for **partial omega squared** indicates that 82% (or a proportion of .82) of the variability on the dependent variable (the number of nonsense syllables correctly recalled) is associated with variability on the levels of the independent variable (noise). Note that because it does not take into account between-subjects variability, **partial omega squared** yields a much higher value than **standard omega squared**.

It was noted in an earlier discussion of **omega squared** (in Section VI of the *t* test for two independent samples) that Cohen (1977; 1988, pp. 284–287) has suggested the following (admittedly arbitrary) values, which are employed in psychology and a number of other disciplines, as guidelines for interpreting $\tilde{\omega}^2$: a) A **small effect size** is one that is greater than .0099 but not more than .0588; b) A **medium effect size** is one that is greater than .0588 but not more than .1379; and c) A **large effect size** is greater than .1379. If one employs Cohen's (1977, 1988) guidelines for magnitude of treatment effect, both $\tilde{\omega}_s^2 = .44$ and $\tilde{\omega}_p^2 = .82$ represent a large treatment effect.

Cohen's *f* index (Test 24h) If the value of **partial omega squared** is substituted in Equation 21.45, **Cohen's *f* index** can be computed. In Section VI of the **single-factor between-subjects analysis of variance**, it was noted that **Cohen's *f* index** is an alternate measure of effect size that can be employed for an analysis of variance. The computation of **Cohen's *f* index** with Equation 21.45 yields the value $f = 2.13$.

$$f = \sqrt{\frac{\tilde{\omega}^2}{1 - \tilde{\omega}^2}} = \sqrt{\frac{.82}{1 - .82}} = 2.13$$

In the discussion of **Cohen's *f* index** in Section VI of the **single-factor between-subjects analysis of variance**, it was noted that Cohen (1977; 1988, pp. 284–288) employed the following (admittedly arbitrary) *f* values as criteria for identifying the magnitude of an effect size: a) A **small effect size** is one that is greater than .1 but not more than .25; b) A **medium effect size** is one that is greater than .25 but not more than .4; and c) A **large effect size** is greater than .4. Employing Cohen's criteria, the value $f = 2.13$ represents a large effect size.

A thorough discussion of the general issues involved in computing a measure of magnitude of treatment effect for a **single-factor within-subjects analysis of variance** can be found in Keppel (1991) and Kirk (1995). Further discussion of the indices of treatment effect discussed in this section, and the relationship between effect size and statistical power can be found in Section IX (the **Addendum**) of the **Pearson product-moment correlation coefficient** under the discussion of **meta-analysis and related topics**.

6. Computation of a confidence interval for the mean of a treatment population Prior to reading this section the reader should review the discussion of confidence intervals in Section VI of both the **single sample *t* test (Test 2)** and the **single-factor between-subjects analysis of variance**. The same procedure employed to compute a confidence interval for a treatment population for the **single-factor between-subjects analysis of variance** is employed for computing

the confidence interval for the mean of a treatment population for a **single-factor within-subjects analysis of variance**. In other words, in order to compute a confidence interval for any experimental treatment/condition, one must conceptualize a within-subjects design as if it was a between-subjects design. The reason for this is that a confidence interval for any single condition will be a function of the variability of the scores of subjects who serve within that condition. Since MS_{res} , the measure of error variability for the repeated-measures analysis of variance, is a measure of within-subjects variability that is independent of any treatment effect, it cannot be employed to estimate the error variability for a specific treatment if one wants to compute a confidence interval for the mean of a treatment population. As is the case with the **single-factor between-subjects analysis of variance**, one can employ either of the following two strategies in computing the confidence interval for a treatment.

a) If one assumes that all of the treatments represent a population with the same variance, Equation 21.48 can be employed to compute the confidence interval (in our example we will assume the 95% confidence interval is being computed). In order to employ Equation 21.48 it is necessary to compute the value of MS_{WG} , which in the case of the **single-factor within-subjects analysis of variance** can be conceptualized as a **within-conditions mean square** (MS_{WC}). In order to compute MS_{WC} , it is necessary to first compute the **within-conditions sum of squares** (SS_{WC}). The latter value is computed employing Equation 24.29 (which is identical to Equation 21.5, except it employs the subscript WC in place of WG).

$$SS_{WC} = \sum_{j=1}^k \left[\sum X_j^2 - \frac{(\sum X_j)^2}{n} \right] \quad (\text{Equation 24.29})$$

$$= \left[443 - \frac{(51)^2}{6} \right] + \left[263 - \frac{(39)^2}{6} \right] + \left[163 - \frac{(29)^2}{6} \right] = 41.83$$

The within-conditions degrees of freedom is computed in an identical manner as is the within-groups degrees of freedom for the **single-factor between-subjects analysis of variance**. Thus, using Equation 21.9 (using the subscript WC in place of WG), $df_{WC} = N - k = 18 - 3 = 15$. The **within-conditions mean square** can now be computed: $MS_{WC} = SS_{WC}/df_{WC} = 41.83/15 = 2.79$. Employing Equation 21.48, the 95% confidence interval for the mean of the population represented by Condition 1 is computed. The value $t_{.05} = 2.13$ is the tabled critical two-tailed $t_{.05}$ value for $df_{WC} = 15$.

$$CI_{.95} = \bar{X}_j \pm t_{df_{WC}} \sqrt{\frac{MS_{WC}}{n}} = 8.5 \pm 2.13 \sqrt{\frac{2.79}{6}} = 8.5 \pm 1.45$$

Thus, the researcher can be 95% confident (or the probability is .95) that the mean of the population represented by Condition 1 falls within the range 7.05 to 9.95. Stated symbolically: $7.05 \leq \mu_1 \leq 9.95$.

b) If one has reason to believe that the treatment in question is distinct from the other treatments, Equation 2.7 can be employed to compute the confidence interval. Specifically, if the mean value of a treatment is substantially above or below the means of the other treatments, it can be argued that one can no longer assume that the treatment shares a common variance with the other treatments. In view of this, one can take the position that the variance of the treatment is the best estimate of the variance of the population represented by that treatment (as opposed to the pooled variability of all of the treatments involved in the study). This position can also be taken even if the means of the k treatments are equal, but the treatments have substantially different estimated population variances.

If Equation 2.7 is employed to compute the 95% confidence interval for the population mean of Condition 1, the estimated variance of the population Condition 1 represents is employed in lieu of the pooled within-conditions variability. In addition, the tabled critical two-tailed $t_{.05}$ value for $df = n - 1 = 5$ (which is $t_{.05} = 2.57$) is employed in the equation. The computation of the confidence interval is illustrated below. Initially, the estimated population standard deviation is computed, which is then substituted in Equation 2.7.

$$\bar{s}_1 = \sqrt{\frac{\sum X_1^2 - \frac{(\sum X_1)^2}{n}}{n - 1}} = \sqrt{\frac{443 - \frac{(51)^2}{6}}{5}} = 1.38$$

$$CI_{.95} \bar{X}_1 \pm t_{.05} \left(\frac{\bar{s}_1}{\sqrt{n}} \right) = 8.5 \pm 2.57 \left(\frac{1.38}{\sqrt{6}} \right) = 8.5 \pm 1.45$$

Thus, the result obtained with Equation 2.7 indicates that the range for $CI_{.95}$ is $7.05 \leq \mu_1 \leq 9.95$.¹⁸ Note that in the case of Condition 1, the confidence intervals computed with Equations 21.48 and 2.7 are identical. This will not always be true, especially when the within-condition variability of the treatment for which the confidence interval is computed is substantially different than the within-condition variability of the other treatments.

VII. Additional Discussion of the Single-Factor Within-Subjects Analysis of Variance

1. Theoretical rationale underlying the single-factor within-subjects analysis of variance

In the **single-factor within-subjects analysis of variance** the total variability can be partitioned into the following two elements: a) **Between-subjects variability** (which is represented by MS_{BS}) represents the variability between the mean scores of the n subjects. In other words, a mean value for each subject who has served in each of the k experimental conditions is computed, and MS_{BS} represents the variance of the n subject means; and b) **Within-subjects variability** (which will be represented by the notation MS_{WS}) represents variability within the k scores of each of the n subjects. In other words, for each subject the variance for that subject's k scores is computed, and the average of the n variances represents within-subjects variability. Within-subjects variability can itself be partitioned into two elements: **between-conditions variability** (which is represented by MS_{BC}) and **residual variability** (which is represented by MS_{res}). Between-conditions variability is essentially a measure of variance of the means of the k experimental conditions. In the **single-factor within-subjects analysis of variance**, it is assumed that any variability between the means of the conditions can be attributed to one or both of the following two elements: 1) **The experimental treatments**; and 2) **Experimental error**. When MS_{BC} (the value computed for between-conditions variability) is significantly greater than MS_{res} (the value computed for error variability), it is interpreted as indicating that a substantial portion of between-conditions variability is due to a treatment effect. The rationale for this is as follows.

Experimental error is random variability in the data that is beyond the control of the researcher. In a within-subjects design the average amount of variability within the k scores of each of the n subjects that cannot be accounted for on the basis of a treatment effect is employed to represent experimental error. Thus, the value computed for MS_{res} is the normal amount of variability that is expected for any subject who serves in each of k experimental conditions, if the conditions are equivalent to one another. Within this framework, residual variability is employed

as a baseline to represent variability which results from factors that are beyond an experimenter's control. The experimenter assumes that even if no treatment effect is present, since such uncontrollable factors are responsible for within-subjects variability, it is logical to assume that they can produce differences of a comparable magnitude between the means of the k experimental conditions. As long as the variability between the condition means (MS_{BC}) is approximately the same as residual variability (MS_{res}), the experimenter can attribute any between-conditions variability present to experimental error. When, however, between-conditions variability is substantially greater than residual variability, it indicates that something over and above error variability is contributing to the variability between the k condition means. In such a case, it is assumed that a treatment effect is responsible for the larger value of MS_{BC} relative to the value of MS_{res} . In essence, if residual variability is subtracted from within-subjects variability, any remaining variability within the scores of subjects can be attributed to a treatment effect. If there is no treatment effect, the result of the subtraction will be zero. Of course, one can never completely rule out the possibility that if MS_{BC} is larger than MS_{res} , the larger value for MS_{BC} is entirely due to error variability. However, since the latter is unlikely, when MS_{BC} is significantly larger than MS_{res} , it is interpreted as indicating the presence of a treatment effect.

Table 24.13 Alternative Summary Table for Analysis of Variance for Example 24.1

Source of variation	SS	df	MS	F
Between-subjects	36.93	5	7.39	
Within-subjects	45.35	12	3.78	
Between-conditions	40.45	2	20.23	41.29
Residual	4.9	10	.49	
Total	82.28	17		

In some sources a table employing the format depicted in Table 24.13 is used to summarize the results of a **single-factor within-subjects analysis of variance**. In contrast to Table 24.2, which does not include a row documenting within-subjects variability, Table 24.13 includes the latter variability, which is partitioned into between-conditions variability and residual variability. In point of fact, it is not necessary to compute the information documented in the row for within-subjects variability in order to compute the F ratio.

Note that in Table 24.13 the following relationships will always be true: a) $SS_T = SS_{BS} + SS_{WS}$; b) $df_T = df_{BS} + df_{WS}$; c) $SS_{WS} = SS_{BC} + SS_{res}$; and d) $df_{WS} = df_{BC} + df_{res}$. The values SS_{WS} , df_{WS} , and MS_{WS} in Table 24.13 are, respectively, computed with Equations 24.30, 24.31, and 24.32.

$$SS_{WS} = \sum X_T^2 - \sum_{i=1}^n \left[\frac{(\sum S_i)^2}{k} \right] \quad (\text{Equation 24.30})$$

$$df_{WS} = n(k - 1) \quad (\text{Equation 24.31})$$

$$MS_{WS} = \frac{SS_{WS}}{df_{WS}} \quad (\text{Equation 24.32})$$

The values $SS_{WS} = 45.35$, $df_{WS} = 12$, and $MS_{WS} = 3.78$ are computed below for Example 24.1.

$$SS_{WS} = 869 - \left[\frac{(20)^2}{3} + \frac{(25)^2}{3} + \frac{(15)^2}{3} + \frac{(25)^2}{3} + \frac{(14)^2}{3} + \frac{(20)^2}{3} \right] = 45.35$$

$$df_{WS} = 6(3 - 1) = 12 \quad MS_{WS} = \frac{45.35}{12} = 3.78$$

Note that $SS_{WS} = SS_{BC} + SS_{res} = 40.45 + 4.9 = 45.35$ and $df_{WS} = df_{BC} + df_{res} = 2 + 10 = 12$.

2. Definitional equations for the single-factor within-subjects analysis of variance In the description of the computational protocol for the **single-factor within-subjects analysis of variance**, Equations 24.2–24.5 are employed to compute the values SS_T , SS_{BC} , SS_{BS} , and SS_{res} . The latter set of computational equations were employed, since they allow for the most efficient computation of the sum of squares values. As noted in Section IV, computational equations are derived from definitional equations which reveal the underlying logic involved in the derivation of the sums of squares. This section will describe the definitional equations for the **single-factor within-subjects analysis of variance**, and apply them to Example 24.1 in order to demonstrate that they yield the same values as the computational equations.

As noted previously, the total sum of squares (SS_T) is made up of two elements, the between-subjects sum of squares (SS_{BS}) and the within-subjects sum of squares (SS_{WS}), and that the latter sum of squares can be partitioned into the between-conditions sum of squares (SS_{BC}) and the residual sum of squares (SS_{res}). The contribution of any single subject's score to the total variability in the data can be expressed in terms of a between-subjects component and a within-subjects component. When the between-subjects component and the within-subjects component are added, the sum reflects that subject's total contribution to the overall variability in the data. The contribution of all N scores to the total variability (SS_T) and the elements that comprise it (SS_{BS} and SS_{WS} , and SS_{BC} and SS_{res} which comprise the latter) are summarized in Table 24.14. The definitional equations described in this section employ the following notation: X_{ij} represents the score of the i^{th} subject in the j^{th} condition, \bar{X}_T represents the grand mean (which is $\bar{X}_T = (\sum_{j=1}^k \sum_{i=1}^n X_{ij}) / N = 119/18 = 6.61$), \bar{X}_j represents the mean of the j^{th} condition, and \bar{S}_i represents the mean of the k scores of the i^{th} subject.

Equation 24.33 is the definitional equation for the **total sum of squares**.¹⁹

$$SS_T = \sum_{j=1}^k \sum_{i=1}^n (X_{ij} - \bar{X}_T)^2 \quad \text{(Equation 24.33)}$$

In employing Equation 24.33 to compute SS_T , the grand mean (\bar{X}_T) is subtracted from each of the N scores and each of the N difference scores is squared. The total sum of squares (SS_T) is the sum of the N squared difference scores. Equation 24.33 is computationally equivalent to Equation 24.2.

Equation 24.34 is the definitional equation for the **between-subjects sum of squares**.

$$SS_{BS} = k \sum_{i=1}^n (\bar{S}_i - \bar{X}_T)^2 \quad \text{(Equation 24.34)}$$

In employing Equation 24.34 to compute SS_{BS} , the following operations are carried out for each of the n subjects. The grand mean (\bar{X}_T) is subtracted from the mean of the subject's k scores. The difference score is squared and the squared difference score is multiplied by the number of experimental conditions (k). After this is done for all n subjects, the values that have

been obtained for each subject as a result of multiplying the squared difference score by k are summed. The resulting value represents the between-subjects sum of squares (SS_{BS}). Equation 24.34 is computationally equivalent to Equation 24.4.

Equation 24.35 is the definitional equation for the **within-subjects sum of squares**.

$$SS_{WS} = \sum_{i=1}^n \sum_{j=1}^k (X_{ij} - \bar{S}_i)^2 \quad (\text{Equation 24.35})$$

In employing Equation 24.35 to compute SS_{WS} , the following operations are carried out for the k scores of each of the n subjects. The mean of a subject's k scores (\bar{S}_i) is subtracted from each of the subject's scores, and the k difference scores for that subject are squared. The sum of the k squared difference scores for all n subjects (i.e., the sum total of N squared difference scores) represents the within-subjects sum of squares (SS_{WS}). Equation 24.35 is computationally equivalent to Equation 24.30.

Equation 24.36 is the definitional equation for the **between-conditions sum of squares**.

$$SS_{BC} = n \sum_{j=1}^k (\bar{X}_j - \bar{X}_T)^2 \quad (\text{Equation 24.36})$$

In employing Equation 24.36 to compute SS_{BC} , the following operations are carried out for each experimental condition. The grand mean (\bar{X}_T) is subtracted from the condition mean (\bar{X}_j). The difference score is squared, and the squared difference score is multiplied by the number of scores in that condition (n). After this is done for all k conditions, the values that have been obtained for each condition as a result of multiplying the squared difference score by the number of subjects in the condition are summed. The resulting value represents the between-conditions sum of squares (SS_{BC}). Equation 24.36 is computationally equivalent to Equation 24.3. An alternative but equivalent method of obtaining SS_{BC} (which is employed in deriving SS_{BC} in Table 24.14) is as follows: Within each condition, for each of the n subjects the grand mean is subtracted from the condition mean, each difference score is squared, and upon doing this for all k conditions, the N squared difference scores are summed.

Equation 24.37 is the definitional equation for the **residual sum of squares**.

$$SS_{res} = \sum_{j=1}^k \sum_{i=1}^n \left[(X_{ij} - \bar{X}_T) - (\bar{S}_i - \bar{X}_T) - (\bar{X}_j - \bar{X}_T) \right]^2 \quad (\text{Equation 24.37})$$

In employing Equation 24.37 to compute SS_{res} , the following operations are carried out for each of the N scores: a) The grand mean (\bar{X}_T) is subtracted from the score (X_{ij}); b) The grand mean (\bar{X}_T) is subtracted from the mean of the k scores for that subject (\bar{S}_i); and c) The grand mean (\bar{X}_T) is subtracted from the mean of the condition from which the score is derived (\bar{X}_j). The value of the difference score obtained in b) is subtracted from the value of the difference score obtained in a), and the difference score obtained in c) is subtracted from the resulting difference. The resulting value is squared, and the sum of the squared values for all N scores represents the residual sum of squares (SS_{res}). Note that in Equation 24.37, for each subject a between-subjects and between-conditions component of variability is subtracted from the subject's contribution to the total variability, resulting in the subject's contribution to the residual variability. Equation 24.37 is computationally equivalent to Equations 24.5/24.6.

Table 24.14 illustrates the use of Equations 24.33–24.37 with the data for Example 24.1.²⁰ In the computations summarized in Table 24.14, the following \bar{S}_i values are employed: $\bar{S}_1 = 20/3 = 6.67$, $\bar{S}_2 = 25/3 = 8.33$, $\bar{S}_3 = 15/3 = 5$, $\bar{S}_4 = 25/3 = 8.33$, $\bar{S}_5 = 14/3 = 4.67$, $\bar{S}_6 = 20/3$

=6.7. The resulting values of SS_T , SS_{BS} , SS_{WS} , SS_{BC} , and SS_{res} are identical to those obtained with the computational equations (Equations 24.2, 24.4, 24.30, 24.3, and 24.5/24.6). Any minimal discrepancies are the result of rounding off error.

Table 24.14 Computation of Sums of Squares for Example 24.1 with Definitional Equations

(Subject, Condition)	X_{ij}	$SS_T = \sum_{j=1}^k \sum_{i=1}^n (X_{ij} - \bar{X}_T)^2$	$SS_{BS} = k \sum_{j=1}^n (\bar{S}_i - \bar{X}_T)^2$	$SS_{WS} = \sum_{j=1}^n \sum_{i=1}^k (X_{ij} - \bar{S}_i)^2$
Condition 1	(1,1)	9 $(9.00-6.61)^2 = 5.71$	$(6.67-6.61)^2 = .00$	$(9.00-6.67)^2 = 5.43$
	(2,1)	10 $(10.00-6.61)^2 = 11.49$	$(8.33-6.61)^2 = 2.96$	$(10.00-8.33)^2 = 2.79$
	(3,1)	7 $(7.00-6.61)^2 = .15$	$(5.00-6.61)^2 = 2.59$	$(7.00-5.00)^2 = 4.00$
	(4,1)	10 $(10.00-6.61)^2 = 11.49$	$(8.33-6.61)^2 = 2.96$	$(10.00-8.33)^2 = 2.79$
	(5,1)	7 $(7.00-6.61)^2 = .15$	$(4.67-6.61)^2 = 3.76$	$(7.00-4.67)^2 = 5.43$
	(6,1)	8 $(8.00-6.61)^2 = 1.93$	$(6.67-6.61)^2 = .00$	$(8.00-6.67)^2 = 1.77$
Condition 2	(1,2)	7 $(7.00-6.61)^2 = .15$	$(6.67-6.61)^2 = .00$	$(7.00-6.67)^2 = .11$
	(2,2)	8 $(8.00-6.61)^2 = 1.93$	$(8.33-6.61)^2 = 2.96$	$(8.00-8.33)^2 = .11$
	(3,2)	5 $(5.00-6.61)^2 = 2.59$	$(5.00-6.61)^2 = 2.59$	$(5.00-5.00)^2 = .00$
	(4,2)	8 $(8.00-6.61)^2 = 1.93$	$(8.33-6.61)^2 = 2.96$	$(8.00-8.33)^2 = .11$
	(5,2)	5 $(5.00-6.61)^2 = 2.59$	$(4.67-6.61)^2 = 3.76$	$(5.00-4.67)^2 = .11$
	(6,2)	6 $(6.00-6.61)^2 = .37$	$(6.67-6.61)^2 = .00$	$(6.00-6.67)^2 = .45$
Condition 3	(1,3)	4 $(4.00-6.61)^2 = 6.81$	$(6.67-6.61)^2 = .00$	$(4.00-6.67)^2 = 7.13$
	(2,3)	7 $(7.00-6.61)^2 = .15$	$(8.33-6.61)^2 = 2.96$	$(7.00-8.33)^2 = 1.77$
	(3,3)	3 $(3.00-6.61)^2 = 13.03$	$(5.00-6.61)^2 = 2.59$	$(3.00-5.00)^2 = 4.00$
	(4,3)	7 $(7.00-6.61)^2 = .15$	$(8.33-6.61)^2 = 2.96$	$(7.00-8.33)^2 = 1.77$
	(5,3)	2 $(2.00-6.61)^2 = 21.25$	$(4.67-6.61)^2 = 3.76$	$(2.00-4.67)^2 = 7.13$
	(6,3)	6 $(6.00-6.61)^2 = .37$	$(6.67-6.61)^2 = .00$	$(6.00-6.67)^2 = .45$
		$SS_T = 82.24$	$SS_{BS} = 36.81$	$SS_{WS} = 45.35$
(Subject, Condition)	X_{ij}	$SS_{BC} = n \sum_{j=1}^k (\bar{X}_j - \bar{X}_T)^2$	$SS_{res} = \sum_{j=1}^k \sum_{i=1}^n [(X_{ij} - \bar{X}_T) - (\bar{S}_i - \bar{X}_T) - (\bar{X}_j - \bar{X}_T)]^2$	
Condition 1	(1,1)	9 $(8.50-6.61)^2 = 3.57$	$[(9.00-6.61)-(6.67-6.61)-(8.50-6.61)]^2 = .19$	
	(2,1)	10 $(8.50-6.61)^2 = 3.57$	$[(10.00-6.61)-(8.33-6.61)-(8.50-6.61)]^2 = .05$	
	(3,1)	7 $(8.50-6.61)^2 = 3.57$	$[(7.00-6.61)-(5.00-6.61)-(8.50-6.61)]^2 = .01$	
	(4,1)	10 $(8.50-6.61)^2 = 3.57$	$[(10.00-6.61)-(8.33-6.61)-(8.50-6.61)]^2 = .05$	
	(5,1)	7 $(8.50-6.61)^2 = 3.57$	$[(7.00-6.61)-(4.67-6.61)-(8.50-6.61)]^2 = .19$	
	(6,1)	8 $(8.50-6.61)^2 = 3.57$	$[(8.00-6.61)-(6.67-6.61)-(8.50-6.61)]^2 = .31$	
Condition 2	(1,2)	7 $(6.50-6.61)^2 = .01$	$[(7.00-6.61)-(6.67-6.61)-(6.50-6.61)]^2 = .19$	
	(2,2)	8 $(6.50-6.61)^2 = .01$	$[(8.00-6.61)-(8.33-6.61)-(6.50-6.61)]^2 = .05$	
	(3,2)	5 $(6.50-6.61)^2 = .01$	$[(5.00-6.61)-(5.00-6.61)-(6.50-6.61)]^2 = .01$	
	(4,2)	8 $(6.50-6.61)^2 = .01$	$[(8.00-6.61)-(8.33-6.61)-(6.50-6.61)]^2 = .05$	
	(5,2)	5 $(6.50-6.61)^2 = .01$	$[(5.00-6.61)-(4.67-6.61)-(6.50-6.61)]^2 = .19$	
	(6,2)	6 $(6.50-6.61)^2 = .01$	$[(6.00-6.61)-(6.67-6.61)-(6.50-6.61)]^2 = .31$	
Condition 3	(1,3)	4 $(4.83-6.61)^2 = 3.17$	$[(4.00-6.61)-(6.67-6.61)-(4.83-6.61)]^2 = .79$	
	(2,3)	7 $(4.83-6.61)^2 = 3.17$	$[(7.00-6.61)-(8.33-6.61)-(4.83-6.61)]^2 = .20$	
	(3,3)	3 $(4.83-6.61)^2 = 3.17$	$[(3.00-6.61)-(5.00-6.61)-(4.83-6.61)]^2 = .05$	
	(4,3)	7 $(4.83-6.61)^2 = 3.17$	$[(7.00-6.61)-(8.33-6.61)-(4.83-6.61)]^2 = .20$	
	(5,3)	2 $(4.83-6.61)^2 = 3.17$	$[(2.00-6.61)-(4.67-6.61)-(4.83-6.61)]^2 = .79$	
	(6,3)	6 $(4.83-6.61)^2 = 3.17$	$[(6.00-6.61)-(6.67-6.61)-(4.83-6.61)]^2 = 1.23$	
		$SS_{BC} = 40.50$	$SS_{res} = 4.86$	

**Table 24.15 Summary Table of Single-Factor
Between-Subjects Analysis of Variance for Example 24.1**

Source of variation	SS	df	MS	F
Between-groups	40.45	2	20.23	7.25
Within-groups	41.83	15	2.79	
Total	82.28	17		

3. Relative power of the single-factor within-subjects analysis of variance and the single-factor between-subjects analysis of variance The use of MS_{res} as the measure of error variability (as opposed to MS_{WC}) for the **single-factor within-subjects analysis of variance** provides for an optimally powerful test of an alternative hypothesis.²¹ The reason why MS_{res} allows for a more powerful test of an alternative hypothesis than MS_{WC} is because when no treatment effect is present in the data, it is expected that the average variability of the k scores of n subjects will be less than the average variability of the scores of n different subjects who serve in any single experimental condition (in an experiment involving k experimental conditions).

To illustrate this point, let us assume that the data for Example 24.1 are obtained in an experiment employing an independent groups/between-subjects design, and as a result of the latter $MS_{\text{WC}} = MS_{\text{WG}}$ is employed as the measure of error variability. Thus, we will assume that each of $N = 18$ subjects is randomly assigned to one of $k = 3$ experimental conditions, resulting in $n = 6$ scores per condition. The data for such an experiment will be evaluated with a **single-factor between-subjects analysis of variance**. In conducting the computations for the latter analysis, the value of SS_T is computed with Equation 21.2 (which, in fact, is identical to Equation 24.2, which is employed to compute SS_T when Example 24.1 is evaluated with a **single-factor within-subjects analysis of variance**). Thus, $SS_T = 82.28$. Equation 21.3, which is employed to compute the between-groups sum of squares (SS_{BG}) is, in fact, identical to Equation 24.3 (which is employed in Section IV to compute the between-conditions sum of squares (SS_{BC})). Thus, $SS_{\text{BG}} = SS_{\text{BC}} = 40.45$. The within-groups sum of squares (SS_{WG}) can be computed with Equation 21.4. Thus, $SS_{\text{WG}} = SS_T - SS_{\text{BG}} = 82.28 - 40.45 = 41.83$. Note that the latter value is identical to the value computed with Equation 24.29 (which as noted earlier is computationally equivalent to Equation 21.5, which yields the same value as Equation 21.4). Employing the values $k = 3$ and $N = 18$ in Equations 21.8–21.10, the values $df_{\text{BG}} = 2$, $df_{\text{WG}} = 15$, and $df_T = 17$ are computed. Substituting the appropriate degrees of freedom in Equations 21.6 and 21.7, the values $MS_{\text{BG}} = 40.45/2 = 20.23$ and $MS_{\text{WG}} = 41.83/15 = 2.79$ are computed. Using Equation 21.12, $F = 20.23/2.79 = 7.25$. Table 24.15 is the summary table of the analysis of variance.

Since $df_{\text{num}} = df_{\text{BG}} = 2$ and $df_{\text{den}} = df_{\text{WG}} = 15$, $F_{.05} = 3.68$ and $F_{.01} = 6.36$ are the critical values in Table A10 that are employed to evaluate the nondirectional alternative hypothesis. Since the obtained value $F = 7.25$ is greater than both of the aforementioned critical values, the alternative hypothesis is supported at both the .05 and .01 levels. Note, however, that the value $F = 7.25$ is substantially less than the value $F = 41.29$, which is obtained when the same set of data is evaluated with the **single-factor within-subjects analysis of variance**. Although the value $F = 7.25$ obtained for a between-subjects analysis is significant at both the .05 and .01 levels, $F = 7.25$ is not very far removed from the tabled critical value $F_{.01} = 6.36$. The value $F = 41.29$, on the other hand, is well above the tabled critical value $F_{.01} = 7.56$ (which is the tabled critical .01 value employed for the **single-factor within-subjects analysis of variance** for $df_{\text{BC}} = 2$ and $df_{\text{res}} = 10$). The fact that the difference between the computed F value and the tabled critical $F_{.01}$ value is much larger when the **single-factor within-subjects analysis of**

variance is employed, illustrates that a within-subjects analysis provides a more powerful test of an alternative hypothesis than a between-subjects analysis.²²

It should be noted that for the same set of data, the tabled critical F value at a given level of significance for a **single-factor between-subjects analysis of variance** will always be lower than the tabled critical F value for a **single-factor within-subjects analysis of variance** (unless there is an extremely large number of scores in each condition, in which case the tabled critical F values for both analyses will be equivalent). This is the case since (as long as n is not extremely large) the number of degrees of freedom associated with the denominator of the F ratio will always be larger for a **single-factor between-subjects analysis of variance** (assuming the values of $n = n_j$ and k for both analyses are equal) than for a **single-factor within-subjects analysis of variance** — i.e., $df_{WG} > df_{res}$. It is important to note, however, that any loss of degrees of freedom associated with a within-subjects analysis will more than likely be offset as a result of employing MS_{res} as the error term in the computation of the F ratio. A final point that should be made is that, if in a within-subjects design, subjects' scores in the k experimental conditions are not correlated with one another (which is highly unlikely), a **single-factor within-subjects analysis of variance** and a **single-factor between-subjects analysis of variance** (as well as a **t test for two dependent samples** and a **t test for two independent samples** when $k = 2$) will yield comparable results.

4. Equivalency of the single-factor within-subjects analysis of variance and the t test for two dependent samples when $k = 2$ Interval/ratio data for an experiment involving $k = 2$ dependent samples can be evaluated with either a **single-factor within-subjects analysis of variance** or a **t test for two dependent samples**. When both of the aforementioned tests are employed to evaluate the same set of data they will yield the same result. Specifically, the following will always be true with respect to the relationship between the computed F and t values for the same set of data: $F = t^2$ and $t = \sqrt{F}$. It will also be the case that the square of the tabled critical t value at a prespecified level of significance for $df = n - 1$ will be equal to the tabled critical F value at the same level of significance for $df_{BC} = 1$ and df_{res} (which will be $df_{res} = (n - 1)(k - 1) = (n - 1)(2 - 1) = n - 1$, which is equivalent to the value $df = n - 1$ employed for the **t test for two dependent samples**).

To illustrate the equivalency of the results obtained with the **single-factor within-subjects analysis of variance** and the **t test for two dependent samples** when $k = 2$, an F value will be computed for Example 17.1. The value $t = 2.86$ is obtained (a more precise value $t = 2.848$ is obtained if all computations are carried out to 3 decimal places) for the latter example when the **t test for two dependent samples** is employed. When the same set of data is evaluated with the **single-factor within-subjects analysis of variance**, the value $F = 8.11$ is computed. Note that $(t = 2.848)^2 = (F = 8.11)$. Equations 24.2–24.5 are employed below to compute the values SS_T , SS_{BC} , SS_{BS} , and SS_{res} for Example 17.1. Since $k = 2$, $n = 10$, and $nk = N = 20$, $df_{BC} = 2 - 1 = 1$, $df_{BS} = 10 - 1 = 9$, $df_{res} = (10 - 1)(2 - 1) = 9$, and $df_T = 20 - 1 = 19$. The full analysis of variance is summarized in Table 24.16.

$$SS_T = 440 - \frac{(78)^2}{20} = 135.8 \quad SS_{BC} = \left[\frac{(47)^2 + (31)^2}{10} \right] - \frac{(78)^2}{20} = 12.8$$

$$SS_{BS} = \left[\frac{(17)^2 + (4)^2 + (4)^2 + (6)^2 + (9)^2 + (4)^2 + (11)^2 + (13)^2 + (9)^2 + (1)^2}{2} \right] - \frac{(78)^2}{20} = 108.8$$

$$SS_{res} = 135.8 - 12.8 - 108.8 = 14.2$$

**Table 24.16 Summary Table of Analysis of Variance
for Example 17.1**

Source of variation	<i>SS</i>	<i>df</i>	<i>MS</i>	<i>F</i>
Between-subjects	108.8	9		
Between-conditions	12.8	1	12.80	8.11
Residual	14.2	9	1.58	
Total	135.8	19		

For $df_{BC} = 1$ and $df_{res} = 9$, the tabled critical .05 and .01 values are $F_{.05} = 5.12$ and $F_{.01} = 10.56$ (which are appropriate for a nondirectional analysis). Note that (if one takes into account rounding off error) the square roots of the aforementioned tabled critical values are (for $df = 9$) the tabled critical two-tailed values $t_{.05} = 2.26$ and $t_{.01} = 3.25$ that are employed in Example 17.1 to evaluate the value $t = 2.86$. Since the obtained value $F = 8.11$ is greater than $F_{.05} = 5.12$ but less than $F_{.01} = 10.56$, the nondirectional alternative hypothesis $H_1: \mu_1 \neq \mu_2$ is supported, but only at the .05 level. The directional alternative hypothesis $H_1: \mu_1 > \mu_2$ is supported at both the .05 and .01 levels, since $F = 8.11$ is greater than the tabled critical one-tailed .05 and .01 values $F_{.05} = 3.36$ and $F_{.01} = 7.95$ (the square roots of which are the tabled critical one-tailed .05 and .01 values $t_{.05} = 1.83$ and $t_{.01} = 2.82$ employed for Example 17.1).²³ The conclusions derived from the **single-factor within-subjects analysis of variance** are identical to those reached when the data are evaluated with the ***t* test for two dependent samples**.

5. The Latin square design Prior to reading this section the reader is advised to review the discussion of **counterbalancing** in Section VII of the ***t* test for two dependent samples**. In the latter section, the subject of **counterbalancing** is discussed within the context of controlling for **order effects**. In a within-subjects design one method of controlling for the potential influence of **practice** or **fatigue** (both of which represent examples of order effects) is by employing what is referred to as a **Latin square design**. The latter type of design (which provides **incomplete counterbalancing**) is more likely to be considered as a reasonable option for controlling for order effects when the independent variable is comprised of many levels (and consequently it becomes prohibitive to employ **complete counterbalancing**). If we conceptualize a within-subjects design as being comprised of n rows (corresponding to each of the n subjects) and k columns (corresponding to each of the k treatments/conditions), we can define a Latin square design as one in which each treatment appears only one time in each row and only one time in each column. Thus, in Table 24.17 there are $n = 4$ subjects and $k = 4$ treatments, and since $n = k$ the configuration of the design is a 4×4 square. The four treatments are identified by the letters **A, B, C, and D**. Subject 1 receives the treatments in the order **A, B, C, D**, Subject 2 receives the treatments in the order **C, A, D, B**, and so on. As noted above, this design does not employ **complete counterbalancing** since, with $k = 4$ treatments, there are $k! = 4! = 24$ possible presentation orders for the treatments. Thus, a minimum of 24 subjects will be required in order to have complete counterbalancing.

Table 24.17 Latin Square Design

		Treatment			
Subject	1	A	B	C	D
	2	C	A	D	B
	3	B	D	A	C
	4	D	C	B	A

The purpose of the Latin square arrangement is to equally distribute any order effects that are present over the k treatments. A Latin square design, however, will only provide effective control for order effects if there is no **interaction** between order of presentation and the treatments. The concept of interaction is discussed in detail in Section V of the **between-subjects factorial analysis of variance (Test 27)**. However, within this context, an interaction between order of presentation and treatment will be present if the performance of subjects on a given treatment is not only a function of the treatment itself, but also depends on which treatments precedes it. In point of fact, the absence of an interaction between order of presentation and treatments is critical in any within-subjects design, since if an interaction is present it will not be possible to obtain a pure measure for any treatment effects that may be present.

Latin square designs can also be utilized for a number of other purposes. One in particular is to control for the influence of what are considered to be potentially **confounding variables** (also referred to as **extraneous** or **nuisance variables**). The interested reader can find detailed discussions of the various applications of Latin square designs in Keppel (1991), Kirk (1982, 1995), Maxwell and Delaney (1990), Myers and Well (1995), and Winer *et al.* (1991).

VIII. Additional Examples Illustrating the Use of the Single-Factor Within-Subjects Analysis of Variance

Since the **single-factor within-subjects analysis of variance** can be employed to evaluate interval/ratio data for any dependent samples design involving two or more experimental conditions, it can be used to evaluate any of the examples that are evaluated with the **t test for two dependent samples** (with the exception of Example 17.2). Examples 24.2–24.6 are, respectively, extensions of Examples 17.1, 17.3, 17.5, 17.7, and 17.6. As is the case with Examples 17.3 and 17.5, Examples 24.3 and 24.4 employ matched subjects, and are thus evaluated as a within-subjects design. Examples 24.6 and 24.7 represent extensions of the **before-after design** to a design involving $k = 3$ experimental conditions. Since the data for all of the examples are identical to the data employed in Example 24.1, they yield the same result.

Example 24.2 *A psychologist conducts a study to determine whether or not people exhibit more emotionality when they are exposed to sexually explicit words, aggressively toned words, or neutral words. Each of six subjects is shown a list of 15 randomly arranged words, which are projected on a screen one at a time for a period of five seconds. Five of the words on the list are sexually explicit, five of the words are aggressively toned, and five of the words are neutral. As each word is projected on the screen, a subject is instructed to say the word softly to him or herself. As a subject does this, sensors attached to the palms of the subject's hands record galvanic skin response (GSR), which is used by the psychologist as a measure of emotionality. The psychologist computes the following three scores for each subject, one score for each of the three experimental conditions: **Condition 1:** GSR/Sexually explicit — The average GSR score for the five sexually explicit words; **Condition 2:** GSR/Aggressively toned — The average GSR score for the five aggressively toned words; **Condition 3:** GSR/Neutral — The average GSR score for the five neutral words. The GSR/Sexually explicit, GSR/Aggressively toned, and GSR/Neutral scores of the six subjects follow. (The higher the score, the higher the level of emotionality.) **Subject 1** (9, 7, 4); **Subject 2** (10, 8, 7); **Subject 3** (7, 5, 3); **Subject 4** (10, 8, 7); **Subject 5** (7, 5, 2); **Subject 6** (8, 6, 6). Do subjects exhibit differences in emotionality with respect to the three categories of words?*

Example 24.3 *A psychologist conducts a study in order to determine whether people exhibit more emotionality when they are exposed to sexually explicit words, aggressively toned words,*

or neutral words. Six sets of identical triplets are employed as subjects and within each set of triplets one member of the set is treated as follows: a) One of the triplets is randomly assigned to Condition 1, in which the subject is shown a list of five sexually explicit words; b) One of the triplets is randomly assigned to Condition 2, in which the subject is shown a list of five aggressively toned words; and c) One of the triplets is randomly assigned to Condition 3, in which the subject is shown a list of five neutral words. As each word is projected on the screen, a subject is instructed to say the word softly to him or herself. As a subject does this, sensors attached to the palms of the subject's hands record galvanic skin response (GSR), which is used by the psychologist as a measure of emotionality. The psychologist computes the following three scores for each set of triplets to represent the emotionality score for each of the experimental conditions: **Condition 1:** GSR/Sexually explicit — The average GSR score for the subject presented with the five sexually explicit words; **Condition 2:** GSR/Aggressively toned — The average GSR score for the subject presented with the five aggressively toned words; **Condition 3:** GSR/Neutral — The average GSR score for the subject presented with the five neutral words. The GSR/Sexually explicit, GSR/Aggressively toned, and GSR/Neutral scores of the six sets of triplets follow. (The first score for each triplet set represents the score of the subject presented with the sexually explicit words, the second score represents the score of the subject presented with the aggressively toned words, and the third score represents the score of the subject presented with the neutral words. The higher the score, the higher the level of emotionality.) **Triplet set 1** (9, 7, 4); **Triplet set 2** (10, 8, 7); **Triplet set 3** (7, 5, 3); **Triplet set 4** (10, 8, 7); **Triplet set 5** (7, 5, 2); **Triplet set 6** (8, 6, 6). Do subjects exhibit differences in emotionality with respect to the three categories of words?

Example 24.4 A researcher wants to assess the impact of different types of punishment on the emotionality of mice. Six sets of mice derived from six separate litters are employed as subjects. Within each set, one of the litter mates is randomly assigned to one of the three experimental conditions. During the course of the experiment each mouse is sequestered in an experimental chamber. While in the chamber, each of the six mice in Condition 1 is periodically presented with a loud noise, and each of the six mice in Condition 2 is periodically presented with a blast of cold air. The six mice in Condition 3 (which is a no treatment control condition) are not exposed to any punishment. The presentation of the punitive stimulus for the animals in Conditions 1 and 2 is generated by a machine that randomly presents the stimulus throughout the duration of the time an animal is in the chamber. The dependent variable of emotionality employed in the study is the number of times each mouse defecates while in the experimental chamber. The number of episodes of defecation for the six sets of mice follows. (The higher the score, the higher the level of emotionality.) **Litter 1** (9, 7, 4); **Litter 2** (10, 8, 7); **Litter 3** (7, 5, 3); **Litter 4** (10, 8, 7); **Litter 5** (7, 5, 2); **Litter 6** (8, 6, 6). Do subjects exhibit differences in emotionality under the different experimental conditions?

Example 24.5 A study is conducted to evaluate the relative efficacy of two drugs (Clearoxin and Lesionoxin) and a placebo on chronic psoriasis. Six subjects afflicted with chronic psoriasis participate in the study. Each subject is exposed to both drugs and the placebo for a six-month period, with a three-month hiatus between treatments. Within the six subjects, the order of presentation of the experimental treatments is completely counterbalanced. The dependent variable employed in the study is a rating of the severity of a subject's lesions under the three experimental conditions. The lower the rating the more severe a subject's psoriasis. The scores of the six subjects under the three treatment conditions follow. (The first score represents the Clearoxin condition (which represents Condition 1), the second score the Lesionoxin condition (which represents Condition 2), and the third score the placebo condition (which represents

Condition 3).) **Subject 1** (9, 7, 4); **Subject 2** (10, 8, 7); **Subject 3** (7, 5, 3); **Subject 4** (10, 8, 7); **Subject 5** (7, 5, 2); **Subject 6** (8, 6, 6). Do the data indicate differences in subjects' responses under the three experimental conditions?

Example 24.6 *In order to assess the efficacy of electroconvulsive therapy (ECT), a psychiatrist evaluates six clinically depressed patients who receive a series of ECT treatments. Each patient is evaluated at the following three points in time: a) One day prior to the first treatment in the ECT series; b) The day following the final treatment in the ECT series; and c) Six months after the final treatment in the ECT series. During each evaluation period a standardized interview is used to operationalize a patient's level of depression, and on the basis of the interview a patient is assigned a score ranging from 0 to 10. The higher a patient's score, the more depressed the patient. The depression scores of the six patients during each of the three time periods follow: **Patient 1** (9, 7, 4); **Patient 2** (10, 8, 7); **Patient 3** (7, 5, 3); **Patient 4** (10, 8, 7); **Patient 5** (7, 5, 2); **Patient 6** (8, 6, 6). Do the data indicate that the ECT is effective, and, if so, is the effect maintained six months after the treatment?*

Although, as described, Example 24.6 can be evaluated with a **single-factor within-subjects analysis of variance**, the design of the study does not allow one to rule out the potential impact of confounding variables. To be more specific, Example 24.6 (which represents an extension of a **before-after design** to more than two measurement periods) does not allow a researcher to draw definitive conclusions with respect to whether any observed changes in mood are, in fact, due to the ECT treatments.²⁴ Thus, even if there is a significant decrease in subjects' depression scores following the final ECT treatment, and the effect is still present six months later, factors other than ECT can account for such a result. As an example, all of the patients may have been depressed about a problem related to the economy, and if, in fact, during the course of the study the economy improves dramatically, the observed changes in mood can be attributed to the improved economy rather than the ECT. In order for the design of the above study to be suitable, it is necessary to include a control group — specifically, a comparable group of depressed patients who are not given ECT (or are given “sham” ECT treatments). By contrasting the depression scores of the control group with those of the treatment group, one can determine whether any observed differences across the three time periods are in fact attributable to the ECT. Inclusion of such a control group would require that the design of the above study be modified into a **mixed factorial design**. The latter design and the analysis of variance employed to evaluate it are discussed in Section IX of the **between-subjects factorial analysis of variance**.

Example 24.7 *In order to assess the efficacy of a drug which a pharmaceutical company claims is effective in treating hyperactivity, six hyperactive children are evaluated during the following three time periods: a) One week prior to taking the drug; b) After a child has taken the drug for six consecutive months; and c) Six months after the drug is discontinued. The children are observed by judges who employ a standardized procedure for evaluating hyperactivity. During each time period a child is assigned a score between 0 and 10, in which the higher the score, the higher the level of hyperactivity. During the evaluation process, the judges are blind with respect to whether or not a child is taking medication at the time he or she is evaluated. The hyperactivity scores of the six children during the three time periods follow: **Child 1**: (9, 7, 4); **Child 2**: (10, 8, 7); **Child 3**: (7, 5, 3); **Child 4**: (10, 8, 7); **Child 5**: (7, 5, 2); **Child 6**: (8, 6, 6). Do the data indicate that the drug is effective?*

Since it lacks a control group, Example 24.7 is subject to the same criticism that is noted for

Example 24.6. Because of the lack of a control group (i.e., a group of hyperactive children who do not receive medication), any observed differences in hyperactivity between two or more of the measurement periods can be the result of extraneous factors in the external environment or physiological/maturational changes in the children that are independent of whether a child is taking the drug. In spite of its limitations, it is not unusual to encounter the use of the design employed in Example 24.7 (which is commonly referred to as an **ABA design**) in behavior modification research. Such designs are most commonly employed with individual subjects in order to assess the efficacy of a treatment protocol. The letters **A** and **B** in an **ABA design** refer to whether or not a treatment is in effect during a specific time period. In Example 24.7, Time period 1 is designated **A** since no treatment is in effect. This initial measure of the subject's behavior provides the researcher with a baseline measure of hyperactivity. During Time period 2, which is designated by the letter **B**, the treatment is in effect. If the treatment is effective, a decrease in hyperactivity in Time period 2 relative to Time period 1 is expected. Time period 3 is once again designated **A**, since the treatment is no longer employed. If, in fact, the treatment is effective it is expected that a subject's level of hyperactivity during Time period 3 will be higher than in Time period 2, and, in fact, return to the baseline level obtained during Time period 1 (unless, of course, the drug has a permanent residual effect). When an **ABA design** is employed with an individual subject, the format of the data resulting from such a study is not suitable for evaluation with an analysis of variance.

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Endnotes

1. A **within-subjects/repeated-measures design** in which each subject serves under each of the k levels of the independent variable is often described as a special case of a **randomized-blocks design**. The term **randomized-blocks design** is most commonly employed to describe a dependent samples design involving matched subjects. As an example, assume that 10 sets of identical triplets are employed in a study to determine the efficacy of two drugs when compared with a placebo. Within each set of triplets one of the members is randomly assigned to each of the three experimental conditions. Such a design is described in various sources as a **matched-subjects/samples design**, a **dependent samples design**, a **correlated-subjects design**, or a **randomized-blocks design**. Within the usage of the term **randomized-blocks design**, each set of triplets constitutes a **block**, and consequently 10 blocks are employed in the study with three subjects in each block.
2. It should be noted that if an experiment is confounded, one cannot conclude that a significant portion of **between-conditions** variability is attributed to the independent variable. This is the case, since if one or more confounding variables systematically vary with the levels of the independent variable, a significant difference can be due to a confounding variable rather than the independent variable.
3. A discussion of counterbalancing can be found in Section VII of the **t test for two dependent samples**).
4. In other words, each subject is tested under one of the six possible presentation orders for the three experimental conditions and, within the sample of six subjects, each of the presentation orders is presented once. Specifically, the following six presentation orders are employed: 1,2,3; 1,3,2; 2,1,3; 2,3,1; 3,1,2; 3,2,1.
5. Although it is possible to conduct a directional analysis, such an analysis will not be described with respect to the analysis of variance. A discussion of a directional analysis when $k = 2$ can be found under the **t test for two dependent samples**. In addition, a discussion of one-tailed F values can be found in Section VI of the **t test for two independent samples** under the discussion of the **Hartley's F_{\max} test for homogeneity of variance/ F test for two population variances (Test 11a)**. A discussion of the evaluation of a directional alternative hypothesis when $k \geq 3$ can be found in Section VII of the **chi-square goodness-of-fit test (Test 8)**. Although the latter discussion is in reference to analysis of a k independent samples design involving categorical data, the general principles regarding analysis of a directional alternative hypothesis when $k \geq 3$ are applicable to the analysis of variance.
6. In Section VII it is noted that the sum of **between-conditions variability** and **residual variability** represents what is referred to as **within-subjects variability**. The sum of squares of **within-subjects variability** (SS_{WS}) is the sum of **between-conditions variability** and **residual variability** — i.e., $SS_{WS} = SS_{BC} + SS_{res}$.

7. Since there is an equal number of scores in each condition, the Equation for SS_{BC} can also be written as follows:

$$SS_{BC} = \left[\frac{(\sum X_1)^2 + (\sum X_2)^2 + \dots + (\sum X_k)^2}{n} \right] - \frac{(\sum X_T)^2}{N}$$

Thus:
$$SS_{BC} = \frac{[(51)^2 + (39)^2 + (29)^2]}{6} - \frac{(119)^2}{18} = 40.45$$

8. The equation for SS_{BS} can also be written as follows:

$$\begin{aligned} SS_{BS} &= \frac{[(\sum S_1)^2 + (\sum S_2)^2 + \dots + (\sum S_n)^2]}{k} - \frac{(\sum X_T)^2}{n} \\ &= \frac{[(20)^2 + (25)^2 + (15)^2 + (14)^2 + (20)^2]}{3} - \frac{(119)^2}{18} = 36.93 \end{aligned}$$

9. In the interest of accuracy, as is the case with the **single-factor between-subjects analysis of variance**, a significant omnibus F value indicates that there is at least one significant difference among all possible comparisons that can be conducted. Thus, it is theoretically possible that none of the simple/pairwise comparisons are significant, and that the significant difference (or differences) involves one or more complex comparisons.
10. As noted in Section VI of the **single-factor between-subjects analysis of variance**, in some instances the $CD_{B/D}$ value associated with the **Bonferroni–Dunn test** will be larger than the CD_S value associated with the **Scheffé test**. However, when there are $c = 3$ comparisons, CD_S will be greater than $CD_{B/D}$.
11. One can, of course, conduct a replication study and base the estimate of MS_{res} on the value of MS_{res} obtained for the comparison in the latter study. In point of fact, one or more replication studies can serve as a basis for obtaining the best possible estimate of error variability to employ for any comparison conducted following an analysis of variance.
12. If the means of each of the conditions for which a composite mean is computed are weighted equally, an even simpler method for computing the composite score of a subject is to add the subject's scores and divide the sum by the number of conditions that are involved. Thus, the composite score of Subject 1 can be obtained by adding 9 and 7 and dividing by 2. The averaging procedure will only work if all of the means are weighted equally. The protocol described in Section VI must be employed in instances where a comparison involves unequal weighting of means.
13. The same result is obtained if (for the three difference scores) the score in the first condition noted is subtracted from the score in the second condition noted (i.e., Condition 2 – Condition 1; Condition 3 – Condition 1; Condition 3 – Condition 2).
14. If the variance of Condition 2 is employed to represent the lowest variance, $r_{X_2 X_3}$ also equals .85.
15. It should be noted that if the accuracy of the probabilities associated with the outcome of

one or more studies is subject to challenge, the accuracy of a pooled probability will be compromised. One can argue, however, that if enough replication studies are conducted, probability inaccuracies in one direction will most likely be balanced by probability inaccuracies in the opposite direction.

16. Inspection of the $df_{\text{res}} = 10$ curve reveals that for $df_{\text{res}} = 10$, a value of approximately $\phi = 3.1$ or greater will be associated with a power of 1.
17. A number of different alternative equations have been proposed for computing **standard omega squared**. Although a slightly different equation was employed in the first edition of this book, it yields approximately the same result that is obtained with Equation 24.25.
18. In using Equation 2.7, \bar{s}_1/\sqrt{n} is equivalent to $s_{\bar{X}_1}$.
19. In employing double (or even more than two) summation signs such as $\sum_{j=1}^k \sum_{i=1}^n$, the mathematical operations specified are carried out beginning with the summation sign that is farthest to the right and continued sequentially with those operations specified by summation signs to the left. Specifically, if $k = 3$ and $n = 6$, the notation $\sum_{j=1}^k \sum_{i=1}^n X_{ij}$ indicates that the sum of the n scores in Condition 1 is computed, after which the sum of the n scores in Condition 2 is computed, after which the sum of the n scores in Condition 3 is computed. The final result will be the sum of all the aforementioned values that have been computed. On the other hand, the notation $\sum_{i=1}^n \sum_{j=1}^k X_{ij}$ indicates that the sum of the $k = 3$ scores of Subject 1 is computed, after which the sum of the $k = 3$ scores of Subject 2 is computed, and so on until the sum of the $k = 3$ scores of Subject 6 is computed. The final result will be the sum of all the aforementioned values that have been computed. In this example the final value computed for $\sum_{j=1}^k \sum_{i=1}^n X_{ij}$ will be equal to the final value computed for $\sum_{i=1}^n \sum_{j=1}^k X_{ij}$. In obtaining the final value, however, the order in which the operations are conducted is reversed. Specifically, in computing $\sum_{j=1}^k \sum_{i=1}^n X_{ij}$, the sums of the k columns are computed and summed in order to arrive at the grand sum, while in computing $\sum_{i=1}^n \sum_{j=1}^k X_{ij}$, the sums of the n rows are computed and summed in order to arrive at the grand sum.
20. For each of the $N = 18$ scores in Table 24.14, the following is true with respect to the contribution of any score to the total variability in the data:

$$(X_{ij} - \bar{X}_T) = (\bar{S}_i - \bar{X}_T) + (X_{ij} - \bar{S}_i)$$

Total deviation score = *BS* deviation score + *WS* deviation score

and

$$(X_{ij} - \bar{S}_i) = (\bar{X}_j - \bar{X}_T) + [(X_{ij} - \bar{X}_T) - (\bar{S}_i - \bar{X}_T) - (\bar{X}_j - \bar{X}_T)]$$

WS deviation score = *BC* deviation score + Residual deviation score

21. As noted in Section VI under the discussion of computation of a confidence interval, MS_{WC} is equivalent to MS_{WG} (which is the analogous measure of variability for the **single-factor between-subjects analysis of variance**).
22. An issue discussed by Keppel (1991) that is relevant to the power of the **single-factor**

within-subjects analysis of variance is that even though counterbalancing is an effective procedure for distributing practice effects evenly over the k experimental conditions in a dependent samples/within-subjects design, if practice effects are, in fact, present in the data, the value of MS_{res} will be inflated, and because of the latter the power of the **single-factor within-subjects analysis of variance** will be reduced. Keppel (1991) describes a methodology for computing an adjusted measure of MS_{res} that is independent of practice effects, which allows for a more powerful test of an alternative hypothesis.

23. In evaluating a directional alternative hypothesis, when $k = 2$ the tabled $F_{.90}$ and $F_{.98}$ values (for the appropriate degrees of freedom) are, respectively, employed as the one-tailed .05 and .01 values. Since the values for $F_{.90}$ and $F_{.98}$ are not listed in [Table A10](#), the values $F_{.90} = 3.36$ and $F_{.98} = 7.95$ can be obtained by squaring the tabled critical one-tailed values $t_{.05} = 1.83$ and $t_{.01} = 2.82$, by employing more extensive tables of the F distribution available in other sources, or through interpolation.
24. Example 24.6 (as well as Example 24.7) can also be viewed as an example of what is commonly referred to as a **time series design** (although time series designs typically involve more measurement periods than are employed in the latter example). The latter design is essentially a **before-after design** involving one or more measurement periods prior to an experimental treatment, and one or more measurement periods following the experimental treatment.

Test 25

The Friedman Two-Way Analysis of Variance by Ranks (Nonparametric Test Employed with Ordinal Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test In a set of k dependent samples (where $k \geq 2$), do at least two of the samples represent populations with different median values?

Relevant background information on test Prior to reading the material on the **Friedman two-way analysis of variance by ranks**, the reader may find it useful to review the general information regarding a dependent samples design contained in Sections I and VII of the ***t* test for two dependent samples (Test 17)**. The **Friedman two-way analysis of variance by ranks** (Friedman (1937)) is employed with ordinal (rank-order) data in a hypothesis testing situation involving a design with two or more dependent samples. The test is an extension of the **binomial sign test for two dependent samples (Test 19)** to a design involving more than two dependent samples and, when $k = 2$, the **Friedman two-way analysis of variance by ranks** will yield a result that is equivalent to that obtained with the **binomial sign test for two dependent samples**.¹ If the result of the **Friedman two-way analysis of variance by ranks** is significant, it indicates there is a significant difference between at least two of the sample medians in the set of k medians. As a result of the latter, the researcher can conclude there is a high likelihood that at least two of the samples represent populations with different median values.

In employing the **Friedman two-way analysis of variance by ranks**, one of the following is true with regard to the rank-order data that are evaluated: a) The data are in a rank-order format, since it is the only format in which scores are available; or b) The data have been transformed into a rank-order format from an interval/ratio format, since the researcher has reason to believe that one or more of the assumptions of the **single-factor within-subjects analysis of variance (Test 24)** (which is the parametric analog of the **Friedman test**) are saliently violated. It should be pointed out that when a researcher elects to transform a set of interval/ratio data into ranks, information is sacrificed. This latter fact accounts for why there is reluctance among some researchers to employ nonparametric tests such as the **Friedman two-way analysis of variance by ranks**, even if there is reason to believe that one or more of the assumptions of the **single-factor within-subjects analysis of variance** have been violated.

Various sources (e.g., Conover (1980, 1999), Daniel (1990)) note that the **Friedman two-way analysis of variance by ranks** is based on the following assumptions: a) The sample of n subjects has been randomly selected from the population it represents; and b) The dependent variable (which is subsequently ranked) is a continuous random variable. In truth, this assumption, which is common to many nonparametric tests, is often not adhered to, in that such tests are often employed with a dependent variable that represents a discrete random variable.

As is the case for other tests that are employed to evaluate data involving two or more dependent samples, in order for the **Friedman two-way analysis of variance by ranks** to generate valid results the following guidelines should be adhered to:² a) To control for order effects,

the presentation of the k experimental conditions should be random or, if appropriate, be counter-balanced; and b) If matched samples are employed, within each set of matched subjects each of the subjects should be randomly assigned to one of the k experimental conditions.

As is noted with respect to other tests that are employed to evaluate a design involving two or more dependent samples, the **Friedman two-way analysis of variance by ranks** can also be used to evaluate a **before-after design**, as well as extensions of the latter design that involve more than two measurement periods. The limitations of the **before-after design** (which are discussed in Section VII of the **t test for two dependent samples**) are also applicable when it is evaluated with the **Friedman two-way analysis of variance by ranks**.

II. Example

Example 25.1 is identical to Example 24.1 (which is evaluated with the **single-factor within-subjects analysis of variance**). In evaluating Example 25.1 it will be assumed that the ratio data (i.e., the number of nonsense syllables correctly recalled) are rank-ordered, since one or more of the assumptions of the **single-factor within-subjects analysis of variance** have been saliently violated.

Example 25.1 *A psychologist conducts a study to determine whether or not noise can inhibit learning. Each of six subjects is tested under three experimental conditions. In each of the experimental conditions a subject is given 20 minutes to memorize a list of 10 nonsense syllables, which the subject is told she will be tested on the following day. The three experimental conditions each subject serves under are as follows: **Condition 1**, the **no noise** condition, requires subjects to study the list of nonsense syllables in a quiet room. **Condition 2**, the **moderate noise** condition, requires subjects to study the list of nonsense syllables while listening to classical music. **Condition 3**, the **extreme noise** condition, requires subjects to study the list of nonsense syllables while listening to rock music. Although in each of the experimental conditions subjects are presented with a different list of nonsense syllables, the three lists are comparable with respect to those variables that are known to influence a person's ability to learn nonsense syllables. To control for order effects, the order of presentation of the three experimental conditions is completely counterbalanced. The number of nonsense syllables correctly recalled by the six subjects under the three experimental conditions follow. (Subjects' scores are listed in the order **Condition 1, Condition 2, Condition 3**.) **Subject 1:** 9, 7, 4; **Subject 2:** 10, 8, 7; **Subject 3:** 7, 5, 3; **Subject 4:** 10, 8, 7; **Subject 5:** 7, 5, 2; **Subject 6:** 8, 6, 6. Do the data indicate that noise influenced subjects' performance?*

III. Null versus Alternative Hypotheses

Null hypothesis

$$H_0: \theta_1 = \theta_2 = \theta_3$$

(The median of the population Condition 1 represents equals the median of the population Condition 2 represents equals the median of the population Condition 3 represents. With respect to the sample data, when the null hypothesis is true the sums of the ranks (as well as the mean ranks) of all k conditions will be equal.)

Alternative hypothesis

$$H_1: \text{Not } H_0$$

(This indicates that there is a difference between at least two of the $k = 3$ population medians. It is important to note that the alternative hypothesis should not be written as follows: $H_1: \theta_1 \neq \theta_2 \neq \theta_3$. The reason why the latter notation for the alternative hypothesis is incorrect

is because it implies that all three population medians must differ from one another in order to reject the null hypothesis. With respect to the sample data, if the alternative hypothesis is true, the sum of the ranks (as well as the mean ranks) of at least two of the k conditions will not be equal. In this book it will be assumed (unless stated otherwise) that the alternative hypothesis for the **Friedman two-way analysis of variance by ranks** is stated **nondirectionally**.³

IV. Test Computations

The data for Example 25.1 are summarized in [Table 25.1](#). The number of subjects employed in the experiment is $n = 6$, and thus within each condition there are $n = n_1 = n_2 = n_3 = 6$ scores. The original interval/ratio scores of the six subjects are recorded in the columns labelled X_1 , X_2 , and X_3 . The adjacent columns R_1 , R_2 , and R_3 note the rank-order assigned to each of the scores.

Table 25.1 Data for Example 25.1

	Condition 1		Condition 2		Condition 3	
	X_1	R_1	X_2	R_2	X_3	R_3
Subject 1	9	3	7	2	4	1
Subject 2	10	3	8	2	7	1
Subject 3	7	3	5	2	3	1
Subject 4	10	3	8	2	7	1
Subject 5	7	3	5	2	2	1
Subject 6	8	3	6	1.5	6	1.5
		$\Sigma R_1 = 18$			$\Sigma R_2 = 11.5$	$\Sigma R_3 = 6.5$
		$\bar{R}_1 = \frac{\Sigma R_1}{n_1} = \frac{18}{6} = 3$			$\bar{R}_2 = \frac{\Sigma R_2}{n_2} = \frac{11.5}{6} = 1.92$	$\bar{R}_3 = \frac{\Sigma R_3}{n_3} = \frac{6.5}{6} = 1.08$

The ranking procedure employed for the **Friedman two-way analysis of variance by ranks** requires that each of the k scores of a subject be ranked within that subject.⁴ Thus, in [Table 25.1](#), for each subject a rank of 1 is assigned to the subject's lowest score, a rank of 2 to the subject's middle score, and a rank of 3 to the subject's highest score. In the event of tied scores, the same protocol described for handling ties for other rank-order tests (discussed in detail in Section IV of the **Mann-Whitney U test (Test 12)**) is employed. Specifically, the average of the ranks involved is assigned to all scores tied for a given rank. The only example of tied scores in Example 25.1 is in the case of Subject 6 who has a score of 6 in both Conditions 2 and 3. In [Table 25.1](#) both of these scores are assigned a rank of 1.5, since if the scores of Subject 6 in Conditions 2 and 3 were not identical, but were still less than the subject's third score (which is 8 in Condition 1), one of the two scores that are, in fact, tied would receive a rank of 1 and the other a rank of 2. The average of these two ranks (i.e., $(1 + 2)/2 = 1.5$) is thus assigned to each of the two tied scores.

It should be noted that it is permissible to reverse the ranking protocol described above. Specifically, one can assign a rank of 1 to a subject's highest score, a rank of 2 to the subject's middle score, and a rank of 3 to the subject's lowest score. This reverse ranking protocol will yield the same value for the **Friedman test** statistic as the protocol employed in [Table 25.1](#).

Upon rank-ordering the scores of the $n = 6$ subjects, the sum of the ranks is computed for each of the experimental conditions. In [Table 25.1](#) the sum of the ranks of the j^{th} condition is represented by the notation ΣR_j . Thus, $\Sigma R_1 = 18$, $\Sigma R_2 = 11.5$, $\Sigma R_3 = 6.5$. Although they are not required for the **Friedman test** computations, the mean rank (\bar{R}_j) for each of the conditions is also noted in [Table 25.1](#).

The chi-square distribution is used to approximate the **Friedman test** statistic. Equation 25.1 is employed to compute the chi-square approximation of the **Friedman test** statistic (which is represented in most sources by the notation χ_r^2).

$$\chi_r^2 = \frac{12}{nk(k+1)} \left[\sum_{j=1}^k (\Sigma R_j)^2 \right] - 3n(k+1) \quad (\text{Equation 25.1})$$

Note that in Equation 25.1 the term $[\sum_{j=1}^k (\Sigma R_j)^2]$ indicates that the sum of the ranks for each of the k experimental conditions is squared, and that the squared sums of ranks are summed. Substituting the appropriate values from Example 25.1 in Equation 25.1, the value $\chi_r^2 = 11.08$ is computed.

$$\chi_r^2 = \frac{12}{(6)(3)(3+1)} [(18)^2 + (11.5)^2 + (6.5)^2] - (3)(6)(3+1) = 11.08$$

V. Interpretation of the Test Results

In order to reject the null hypothesis, the computed value χ_r^2 must be equal to or greater than the tabled critical chi-square value at the prespecified level of significance. The computed chi-square value is evaluated with **Table A4 (Table of the Chi-Square Distribution)** in the **Appendix**. For the appropriate degrees of freedom, the tabled $\chi_{.95}^2$ value (which is the chi-square value at the 95th percentile) and the tabled $\chi_{.99}^2$ value (which is the chi-square value at the 99th percentile) are employed as the .05 and .01 critical values for evaluating a nondirectional alternative hypothesis. The number of degrees of freedom employed in the analysis are computed with Equation 25.2. Thus, $df = 3 - 1 = 2$.

$$df = k - 1 \quad (\text{Equation 25.2})$$

For $df = 2$, the tabled critical .05 and .01 chi-square values are $\chi_{.05}^2 = 5.99$ and $\chi_{.01}^2 = 9.21$. Since the computed value $\chi_r^2 = 11.08$ is greater than $\chi_{.05}^2 = 5.99$ and $\chi_{.01}^2 = 9.21$, the alternative hypothesis is supported at both the .05 and .01 levels.⁵ A summary of the analysis of Example 25.1 with the **Friedman two-way analysis of variance by ranks** follows: It can be concluded that there is a significant difference between at least two of the three experimental conditions exposed to different levels of noise. This result can be summarized as follows: $\chi_r^2(2) = 11.08, p < .01$.

It should be noted that when the data for Example 25.1 are evaluated with a **single-factor within-subjects analysis of variance**, the null hypothesis can also be rejected at both the .05 and .01 levels. The reader should note, however, that the difference between the value $\chi_r^2 = 11.08$ (obtained for the **Friedman test**) and $\chi_{.01}^2 = 9.21$ (the .01 tabled critical value for the **Friedman test**) is much smaller than the difference between $F = 41.29$ (obtained for the analysis of variance) and $F_{.01} = 7.56$ (the .01 tabled critical value for the analysis of variance). The smaller difference between the computed test statistic and the tabled critical value in the case of the **Friedman test** reflects the fact that, as a general rule (assuming that none of the assumptions of the analysis of variance are saliently violated), it provides a less powerful test of an alternative hypothesis than the analysis of variance.

VI. Additional Analytical Procedures for the Friedman Two-Way Analysis of Variance by Ranks and/or Related Tests

1. Tie correction for the Friedman two-way analysis of variance by ranks Some sources recommend that if there is an excessive number of ties in the overall distribution of scores, the value of the **Friedman test** statistic be adjusted. The tie correction results in a small increase in the value of χ_r^2 (thus providing a slightly more powerful test of the alternative hypothesis). Equation 25.3 (based on a methodology described in Daniel (1990) and Marascuilo and McSweeney (1977)) is employed in computing the value C , which represents the tie correction factor for the **Friedman two-way analysis of variance by ranks**.

$$C = 1 - \frac{\sum_{i=1}^s (t_i^3 - t_i)}{n(k^3 - k)} \quad (\text{Equation 25.3})$$

Where: s = the number of sets of ties
 t_i = the number of tied scores in the i^{th} set of ties

The notation $\sum_{i=1}^s (t_i^3 - t_i)$ indicates the following: a) For each set of ties, the number of ties in the set is subtracted from the cube of the number of ties in that set; and b) The sum of all the values computed in part a) is obtained. The tie correction will now be computed for Example 25.1. In the latter example there is $s = 1$ set of ties in which there are $t_i = 2$ ties (i.e., the two scores of 6 for Subject 6 under Conditions 2 and 3). Thus:

$$\sum_{i=1}^s (t_i^3 - t_i) = [(2)^3 - 2] = 6$$

Employing Equation 25.3, the value $C = .958$ is computed.

$$C = 1 - \frac{6}{6[(3)^3 - 3]} = .958$$

$\chi_{r_c}^2$, which represents the tie-corrected value of the **Friedman test** statistic, is computed with Equation 25.4.

$$\chi_{r_c}^2 = \frac{\chi_r^2}{C} \quad (\text{Equation 25.4})$$

Employing Equation 25.4, the tie-corrected value $\chi_{r_c}^2 = 11.57$ is computed.

$$\chi_{r_c}^2 = \frac{11.08}{.958} = 11.57$$

As is the case with $\chi_r^2 = 11.08$ computed with Equation 25.1, the value $\chi_{r_c}^2 = 11.57$ computed with Equation 25.4 is significant at both the .05 and .01 levels (since it is greater than $\chi_{.05}^2 = 5.99$ and $\chi_{.01}^2 = 9.21$). Although Equation 25.4 results in a slightly less conservative test than Equation 25.1, in this instance the two equations lead to identical conclusions with respect to the null hypothesis.

2. Pairwise comparisons following computation of the test statistic for the Friedman two-way analysis of variance by ranks Prior to reading this section the reader should review the discussion of comparisons in Section VI of the **single-factor between-subjects analysis of variance (Test 21)**. As is the case with the omnibus F value computed for an analysis of variance, the χ_r^2 value computed with Equation 25.1 is based on an evaluation of all k experimental conditions. When the value of χ_r^2 is significant, it does not indicate whether just two or, in fact, more than two conditions differ significantly from one another. In order to answer the latter question, it is necessary to conduct comparisons contrasting specific conditions with one another. This section will describe methodologies that can be employed for conducting **simple/ pairwise comparisons** following the computation of a χ_r^2 value.⁶

In conducting a simple comparison, the null hypothesis and nondirectional alternative hypothesis are as follows: $H_0: \theta_a = \theta_b$ versus $H_1: \theta_a \neq \theta_b$. In the aforementioned hypotheses, θ_a and θ_b represent the medians of the populations represented by the two conditions involved in the comparison. The alternative hypothesis can also be stated directionally as follows: $H_1: \theta_a > \theta_b$ or $H_1: \theta_a < \theta_b$.

Various sources (e.g., Daniel (1990) and Siegel and Castellan (1988)) describe a comparison procedure for the **Friedman two-way analysis of variance by ranks** (which is essentially the application of the **Bonferroni-Dunn method** described in Section VI of the **single-factor between-subjects analysis of variance** to the **Friedman test** model). Through use of Equation 25.5, the procedure allows a researcher to identify the minimum required difference between the sums of the ranks of any two conditions (designated as CD_F) in order for them to differ from one another at the prespecified level of significance.⁷

$$CD_F = z_{\text{adj}} \sqrt{\frac{nk(k+1)}{6}} \quad (\text{Equation 25.5})$$

The value of z_{adj} is obtained from **Table A1 (Table of the Normal Distribution)** in the **Appendix**. In the case of a nondirectional alternative hypothesis, z_{adj} is the z value above which a proportion of cases corresponding to the value $\alpha_{FW}/2c$ falls (where c is the total number of comparisons that are conducted). In the case of a directional alternative hypothesis, z_{adj} is the z value above which a proportion of cases corresponding to the value α_{FW}/c falls. When all possible pairwise comparisons are made $c = [k(k-1)]/2$, and thus, $2c = k(k-1)$. In Example 25.1 the number of pairwise/simple comparisons that can be conducted are $c = [3(3-1)]/2 = 3$ — specifically, Condition 1 versus Condition 2, Condition 1 versus Condition 3, and Condition 2 versus Condition 3.

The value of z_{adj} will be a function of both the maximum **familywise Type I error rate** (α_{FW}) the researcher is willing to tolerate and the total number of comparisons that are conducted. When a limited number of comparisons are planned prior to collecting the data, most sources take the position that a researcher is not obliged to control the value of α_{FW} . In such a case, the **per comparison Type I error rate** (α_{PC}) will be equal to the prespecified value of alpha. When α_{FW} is not adjusted, the value of z_{adj} employed in Equation 25.5 will be the tabled critical z value that corresponds to the prespecified level of significance. Thus, if a nondirectional alternative hypothesis is employed and $\alpha = \alpha_{PC} = .05$, the tabled critical two-tailed .05 value $z_{.05} = 1.96$ is used to represent z_{adj} in Equation 25.5. If $\alpha = \alpha_{PC} = .01$, the tabled critical two-tailed .01 value $z_{.01} = 2.58$ is used in Equation 25.5. In the same respect, if a directional alternative hypothesis is employed, the tabled critical .05 and .01 one-tailed values $z_{.05} = 1.65$ and $z_{.01} = 2.33$ are used for z_{adj} in Equation 25.5.

When comparisons are not planned beforehand, it is generally acknowledged that the value

of α_{FW} must be controlled so as not to become excessive. The general approach for controlling the latter value is to establish a **per comparison Type I error rate** which insures that α_{FW} will not exceed some maximum value stipulated by the researcher. One method for doing this (described under the **single-factor between-subjects analysis of variance** as the **Bonferroni–Dunn method**) establishes the **per comparison Type I error rate** by dividing the maximum value one will tolerate for the **familywise Type I error rate** by the total number of comparisons conducted. Thus, in Example 25.1, if one intends to conduct all three pairwise comparisons and wants to insure that α_{FW} does not exceed .05, $\alpha_{PC} = \alpha_{FW}/c = .05/3 = .0167$. The latter proportion is used to determine the value of z_{adj} . As noted earlier, if a directional alternative hypothesis is employed for a comparison, the value of z_{adj} employed in Equation 25.5 is the z value above which a proportion equal to $\alpha_{PC} = \alpha_{FW}/c$ of the cases falls. In **Table A1**, the z value that corresponds to the proportion .0167 is $z = 2.13$. By employing $z_{adj} = 2.13$ in Equation 25.5, one can be assured that within the “family” of three pairwise comparisons, α_{FW} will not exceed .05 (assuming all of the comparisons are directional). If a nondirectional alternative hypothesis is employed for all of the comparisons, the value of z_{adj} will be the z value above which a proportion equal to $\alpha_{FW}/2c = \alpha_{PC}/2$ of the cases falls. Since $\alpha_{PC}/2 = .0167/2 = .0083$, $z = 2.39$. By employing $z_{adj} = 2.39$ in Equation 25.5, one can be assured that α_{FW} will not exceed .05.⁸

In order to employ the CD_F value computed with Equation 25.5, it is necessary to determine the absolute value of the difference between the sums of the ranks of each pair of experimental conditions that are compared.⁹ **Table 25.2** summarizes the difference scores between pairs of sums of ranks.

Table 25.2 Difference Scores Between Pairs of Sums of Ranks for Example 25.1

$ \Sigma R_1 - \Sigma R_2 = 18 - 11.5 = 6.5$
$ \Sigma R_1 - \Sigma R_3 = 18 - 6.5 = 11.5$
$ \Sigma R_2 - \Sigma R_3 = 11.5 - 6.5 = 5$

If any of the differences between the sums of ranks is equal to or greater than the CD_F value computed with Equation 25.5, a comparison is declared significant. Equation 25.5 will now be employed to evaluate the nondirectional alternative hypothesis $H_1: \theta_a \neq \theta_b$ for all three pairwise comparisons. Since it will be assumed that the comparisons are unplanned and that the researcher does not want the value of α_{FW} to exceed .05, the value $z_{adj} = 2.39$ will be used in computing CD_F .

$$CD_F = (2.39) \sqrt{\frac{(6)(3)(3 + 1)}{6}} = (2.39)(3.46) = 8.28$$

The obtained value $CD_F = 8.28$ indicates that any difference between the sums of ranks of two conditions that is equal to or greater than 8.28 is significant. With respect to the three pairwise comparisons, the only difference between the sum of ranks of two conditions which is greater than $CD_F = 8.28$ is $|\Sigma R_1 - \Sigma R_3| = 11.5$. Thus, we can conclude there is a significant difference between Condition 1 and Condition 3. We cannot conclude that the difference between any other pair of conditions is significant.

An alternative strategy that can be employed for conducting pairwise comparisons for the **Friedman test** model is to use one of the tests that are described for evaluating a dependent samples design involving $k = 2$ samples. Specifically, one can employ either the **Wilcoxon**

matched-pairs signed-ranks test (Test 18) or the **binomial sign test for two dependent samples**. Whereas the **binomial sign test** only takes into consideration the direction of the difference of subjects' scores in the two experimental conditions, the **Wilcoxon test** rank-orders the interval/ratio difference scores of subjects. Because of the latter, the **Wilcoxon test** employs more information than the **binomial sign test**, and, consequently, will provide a more powerful test of an alternative hypothesis. Both the **Wilcoxon test** and **binomial sign test** will be used to conduct the three pairwise comparisons for Example 25.1.¹⁰

Use of the **Wilcoxon matched-pairs signed-ranks test** requires that for each comparison that is conducted the difference scores of subjects in the two experimental conditions be rank-ordered, and that the Wilcoxon T statistic be computed for that comparison. The exact distribution of the **Wilcoxon test** statistic can only be used when the value of α_{PC} is equal to one of the probabilities documented in **Table A5 (Table of Critical T Values for Wilcoxon's Signed-Ranks and Matched-Pairs Signed-Ranks Tests)** in the **Appendix**. When α_{PC} is a value other than those listed in **Table A5**, the normal approximation of the **Wilcoxon test** statistic must be employed.

When the **Wilcoxon matched-pairs signed-ranks test** is employed for the three pairwise comparisons, the following T values are computed: a) Condition 1 versus Condition 2: $T = 0$; b) Condition 1 versus Condition 3: $T = 0$; and c) Condition 2 versus Condition 3: $T = 0$.¹¹ When the aforementioned T values are substituted in Equations 18.2 and 18.3 (the uncorrected and continuity-corrected normal approximations for the **Wilcoxon test**), the following absolute z values are computed: a) Condition 1 versus Condition 2: $z = 2.20$ and $z = 2.10$; b) Condition 1 versus Condition 3: $z = 2.20$ and $z = 2.10$; and c) Condition 2 versus Condition 3: $z = 2.02$ and $z = 1.89$. If we want to evaluate a nondirectional alternative hypothesis and insure that α_{FW} does not exceed .05, the value of α_{PC} is set equal to .0167. **Table A5** cannot be employed, since it does not list two-tailed critical T values for $\alpha_{.0167}$. In order to evaluate the result of the normal approximation, we identify the tabled critical two-tailed .0167 z value in **Table A1**. In employing Equation 25.5 earlier in this section, we determined that the latter value is $z_{.0167} = 2.39$. Since none of the z values computed for the normal approximation is equal to or greater than $z_{.0167} = 2.39$, none of the pairwise comparisons is significant. This result is not identical to that obtained with Equation 25.5, in which case a significant difference is computed for the comparison Condition 1 versus Condition 3. Although the latter comparison (as well as the Condition 1 versus Condition 2 comparison) comes close when it is evaluated with the **Wilcoxon test**, it falls just short of achieving significance.

In the event the researcher elects not to control the value of α_{FW} and employs $\alpha_{PC} = .05$ in evaluating the three pairwise comparisons (once again assuming a nondirectional analysis), both the Condition 1 versus Condition 2 and Condition 1 versus Condition 3 comparisons are significant at the .05 level if the **Wilcoxon test** is employed. Specifically, both the uncorrected and corrected normal approximations are significant, since $z = 2.20$ and $z = 2.10$ (computed for both the Condition 1 versus Condition 2 and Condition 1 versus Condition 3 comparisons) are greater than the tabled critical two-tailed value $z_{.05} = 1.96$. The Condition 2 versus Condition 3 comparison is also significant, but only if the uncorrected value $z = 2.02$ is employed. Employing **Table A5**, we also determine that both the Condition 1 versus Condition 2 and Condition 1 versus Condition 3 comparisons are significant at the .05 level, since the computed value $T = 0$ for both comparisons is equal to the tabled critical two-tailed .05 value $T_{.05} = 0$ (for $n = 6$). The Condition 2 versus Condition 3 comparison is not significant, since no two-tailed .05 critical value is listed in **Table A5** for $n = 5$. If Equation 25.5 is employed for the same set of comparisons, however, only the Condition 1 versus Condition 3 comparison is significant. This is the case, since $CD_F = (1.96)(3.46) = 6.78$, and only the difference $|\sum R_1 - \sum R_3| = 11.5$ is greater than $CD_F = 6.78$.¹² The difference $|\sum R_1 - \sum R_2| = 6.5$ (which is significant with the

Wilcoxon test) just falls short of achieving significance. Although the result obtained with Equation 25.5 is not identical to that obtained with the **Wilcoxon test**, the two analyses are reasonably consistent with one another.

In the event the **binomial signed test for two dependent samples** is employed to conduct comparisons, a researcher must determine for each comparison the number of subjects who yield positive versus negative difference scores. With the exception of Subject 6 in the Condition 2 versus Condition 3 comparison, all of the difference scores for the three pairwise comparisons are positive (since all subjects obtain a higher score in Condition 1 than Condition 2, in Condition 1 than Condition 3, and in Condition 2 than Condition 3). For the Condition 1 versus Condition 2 and Condition 1 versus Condition 3 comparisons, we must compute $P(x = 6)$ for $n = 6$. For the Condition 2 versus Condition 3 comparison (which does not include Subject 6 in the analysis, since the latter subject has a zero difference score), we must compute $P(x = 5)$ for $n = 5$. For all three pairwise comparisons $\pi_+ = \pi_- = .5$.

Employing **Table A6 (Table of the Binomial Distribution, Individual Probabilities)** (or **Table A7**) in the **Appendix** we can determine that when $n = 6$, $P(x = 6) = .0156$. Thus, the computed two-tailed probability for the Condition 1 versus Condition 2 and Condition 1 versus Condition 3 comparisons is $(2)(.0156) = .0312$. When $n = 5$, $P(x = 5) = .0312$. The computed two-tailed probability for the Condition 2 versus Condition 3 comparison is $(2)(.0312) = .0624$.

As before, if we want to evaluate a nondirectional alternative hypothesis and insure that α_{FW} does not exceed .05, the value of α_{PC} is set equal to .0167. Thus, in order to reject the null hypothesis the computed two-tailed binomial probability for a comparison must be equal to or less than .0167. Since the computed two-tailed probabilities .0312 (for the Condition 1 versus Condition 2 and the Condition 1 versus Condition 3 comparisons) and .0624 (for the Condition 2 versus Condition 3 comparison) are greater than .0167, none of the pairwise comparisons is significant.

In the event the researcher elects not to control the value of α_{FW} and employs $\alpha_{PC} = .05$ for evaluating the three pairwise comparisons (once again assuming a nondirectional analysis), both the Condition 1 versus Condition 2 and Condition 1 versus Condition 3 comparisons are significant at the .05 level, since the computed two-tailed probability .0312 (for the Condition 1 versus Condition 2 and the Condition 1 versus Condition 3 comparisons) is less than .05. The Condition 2 versus Condition 3 comparison is not significant, since the computed two-tailed probability .0624 for the latter comparison is greater than .05.

When the results obtained with the **binomial sign test** are compared with those obtained with Equation 25.5 and the **Wilcoxon test**, it would appear that of the three procedures the **binomial sign test** results in the most conservative test (and thus, as noted previously, the least powerful test). However, if one takes into account the obtained binomial probabilities, they are, in actuality, not far removed from the probabilities obtained when Equation 25.5 and the **Wilcoxon test** are used.

In the case of Example 25.1, regardless of which comparison procedure one employs, it would appear that unless one uses a very low value for α_{PC} , the Condition 1 versus Condition 3 comparison is significant. There is some suggestion that the Condition 1 versus Condition 2 comparison may also be significant, but some researchers would recommend conducting additional studies in order to clarify whether or not the two conditions represent different populations. Although based on the analyses that have been conducted the Condition 2 versus Condition 3 comparison does not appear to be significant, it is worth noting that if the researcher uses the **Wilcoxon test** (specifically, the normal approximation not corrected for continuity) to evaluate the directional alternative hypothesis $H_1: \theta_2 > \theta_3$ with $\alpha_{PC} = .05$, the latter comparison also yields a significant result. Thus, further studies might be in order to clarify the relationship between the populations represented by Conditions 2 and 3.

The intent of presenting three comparison procedures in this section is to illustrate that, generally speaking, the results obtained with the different comparison procedures will be reasonably consistent with one another. As is noted in the discussion of comparisons in Section VI of both the **single-factor between-subjects analysis of variance** and the **Kruskal–Wallis one-way analysis of variance by ranks** (see Endnote 7 of the latter test), in instances where two or more comparison procedures yield inconsistent results, the most effective way to resolve such a problem is by conducting one or more replication studies. By doing the latter, a researcher should be able to clarify whether or not an obtained difference is reliable, as well as the magnitude of the difference (if, in fact, one exists).

It is also noted throughout the book that, in the final analysis, the decision regarding which of the available comparison procedures to employ is usually not the most important issue facing the researcher conducting comparisons. The main issue is what maximum value one is willing to tolerate for α_{FW} . Additional sources on comparison procedures for the **Friedman test** model are Church and Wike (1979) (who provide a comparative analysis of a number of different comparison procedures); Conover (1980, 1999) (who employs an equation that computes a CD_F value that is different from the one obtained with Equation 25.5); Daniel (1990) (who describes a methodology for comparing $(k - 1)$ conditions with a control group, as well as a methodology for estimating the size of a difference between the medians of any pair of experimental conditions); Marascuilo and McSweeney (1977) (who within the framework of a comprehensive discussion of the **Friedman test** model describe a methodology for conducting complex comparisons); and Siegel and Castellan (1988) (who also describe the methodology for comparing $(k - 1)$ conditions with a control group).

Marascuilo and McSweeney (1977) also discuss the computation of a confidence interval for a comparison for the **Friedman test** model. One approach for computing a confidence interval is to add to and subtract the computed value of CD_F from the obtained difference between the sums of ranks (or mean ranks, if the equation in Endnote 7 is employed) involved in the comparison. The latter approach is based on the same logic employed for computing a confidence interval for a comparison in Section VI of the **single-factor between-subjects analysis of variance**.

VII. Additional Discussion of the Friedman Two-Way Analysis of Variance by Ranks

1. Exact tables of the Friedman distribution Although an exact probability value can be computed for obtaining a configuration of ranks that is equivalent to or more extreme than the configuration observed in the data evaluated with the **Friedman two-way analysis of variance by ranks**, the chi-square distribution is generally employed to estimate the latter probability. Although most sources employ the chi-square approximation regardless of the values of k and n , some sources recommend that exact tables be employed when the values of n and/or k are small. The exact sampling distribution for the **Friedman two-way analysis of variance by ranks** is based on the use of **Fisher's method of randomization** (which is discussed in Section IX (the **Addendum**) of the **Mann-Whitney U test**).

Tables of exact critical values, which can be viewed as adjusted chi-square values, can be found in Marascuilo and McSweeney (1977) and Siegel and Castellan (1988) (who list critical values for various values of n between 5 and 13 when the value of k is between 3 and 5). Depending upon the values of k and n , exact critical values may be either slightly larger or smaller than the critical chi-square values in **Table A4**. In point of fact, for $k = 3$ and $n = 6$ the exact tabled critical .05 and .01 values for the **Friedman test** statistic are respectively $\chi^2_{r,.05} = 7.00$ and $\chi^2_{r,.01} = 9.00$. Since the value $\chi^2_r = 11.08$ computed for Example 25.1 is greater than both

of the aforementioned critical values, the null hypothesis can still be rejected at both the .05 and .01 levels. Although the conclusions with respect to Example 25.1 are the same regardless of whether one employs the exact critical values or the chi-square values in [Table A4](#), inspection of the two sets of values indicates that the exact .05 critical value is larger than the corresponding critical value $\chi^2_{.05} = 5.99$ derived from [Table A4](#), while the reverse is true with respect to the exact .01 critical value, which is less than the corresponding value $\chi^2_{.01} = 9.21$ in [Table A4](#). It should be noted that for a given value of k , as the value of n increases, the exact critical value approaches the tabled chi-square value in [Table A4](#). An additional point of interest relevant to evaluating the **Friedman test** statistic, is that Daniel (1990) and Conover (1980, 1999) cite a study by Iman and Davenport (1980) which suggests that the F distribution can be used to approximate the sampling distribution for the **Friedman test**, and that the latter approximation may be more accurate than the more commonly employed chi-square approximation.

2. Equivalency of the Friedman two-way analysis of variance by ranks and the binomial sign test for two dependent samples when $k = 2$ In Section I it is noted that when $k = 2$ the **Friedman two-way analysis of variance by ranks** will yield a result that is equivalent to that obtained with the **binomial sign test for two dependent samples**. To be more specific, the **Friedman test** will yield a result that is equivalent to the normal approximation of the **binomial sign test for two dependent samples** when the correction for continuity is not employed (i.e., the result obtained with Equation 19.3).¹³ It should be noted, however, that the two tests will only yield an equivalent result when none of the subjects has the same score in the two experimental conditions. In the case of the **binomial sign test**, any subject who has the same score in both conditions is eliminated from the data analysis. In the case of the **Friedman test**, however, such subjects are included in the analysis. In order to demonstrate the equivalency of the two tests, Equation 25.1 will be employed to analyze the data for Example 19.1 (which was previously evaluated with the **binomial sign test for two dependent samples**). In using Equation 25.1 the data for Subject 2 are not included, since the latter subject has identical scores in both conditions. Thus, in our analysis $n = 9$ and $k = 2$. [Table 25.3](#) summarizes the rank-ordering of data for Example 19.1 within the framework of the **Friedman test** model.

Table 25.3 Summary of Data for Example 19.1 for Friedman Test Model

	Condition 1		Condition 2	
	X_1	R_1	X_2	R_2
Subject 1	9	2	8	1
Subject 2	2	1.5	2	1.5
Subject 3	1	1	3	2
Subject 4	4	2	2	1
Subject 5	6	2	3	1
Subject 6	4	2	0	1
Subject 7	7	2	4	1
Subject 8	8	2	5	1
Subject 9	5	2	4	1
Subject 10	1	2	0	1
		$\Sigma R_1 = 18.5$	$\Sigma R_2 = 11.5$	

Since the data for Subject 2 are not included in the analysis, the rank-orders for Subject 2 under the two conditions are subtracted from the values $\Sigma R_1 = 18.5$ and $\Sigma R_2 = 11.5$, yielding the revised values $\Sigma R_1 = 17$ and $\Sigma R_2 = 10$ which are employed in Equation 25.1. Employing

the latter equation, the value $\chi_r^2 = 5.44$ is computed.

$$\chi_r^2 = \frac{12}{(9)(2)(2 + 1)} [(17)^2 + (10)^2] - (3)(9)(3) = 5.44$$

Employing Equation 25.2, $df = 2 - 1 = 1$. For $df = 1$, the tabled critical .05 and .01 chi-square values are $\chi_{.05}^2 = 3.84$ and $\chi_{.01}^2 = 6.63$. Since the obtained value $\chi_r^2 = 5.44$ is greater than $\chi_{.05}^2 = 3.84$, the alternative hypothesis is supported at the .05 level. It is not, however, supported at the .01 level, since $\chi_r^2 = 5.44$ is less than $\chi_{.01}^2 = 6.63$.¹⁴

Equation 19.3 yields the value $z = 2.33$ for the same set of data. Since the square of a z value will equal the corresponding chi-square value computed for the same set of data, z^2 should equal χ_r^2 . In point of fact, $(z = 2.33)^2 = (\chi_r^2 = 5.44)$ (the minimal discrepancy is due to rounding off error). It is also the case that the square of the tabled critical z value employed for the normal approximation of the **binomial sign test for two dependent samples** will always equal the tabled critical chi-square value employed for the **Friedman test** at the same level of significance. Thus, the square of the tabled critical two-tailed value $z_{.05} = 1.96$ employed for the normal approximation of the **binomial sign test** equals $\chi_{.05}^2 = 3.84$ employed for the **Friedman test** (i.e., $(z = 1.96)^2 = (\chi^2 = 3.84)$).

3. Power-efficiency of the Friedman two-way analysis of variance by ranks Daniel (1989) notes that Noether (1967) states when the underlying population distributions are normal, the **asymptotic relative efficiency** (which is discussed in Section VII of the **Wilcoxon signed-ranks test (Test 6)**) of the **Friedman two-way analysis of variance by ranks** (relative to the **single-factor within-subjects analysis of variance**) is $.955k/(k + 1)$. Thus, when $k = 2$ the asymptotic relative efficiency of the **Friedman test** is .64, but when $k = 10$ it equals .87. For a uniform distribution, the asymptotic relative efficiency of the **Friedman test** is $k/(k + 1)$.

4. Alternative nonparametric rank-order procedures for evaluating a design involving k dependent samples In addition to the **Friedman two-way analysis of variance by ranks**, a number of other nonparametric procedures for two or more dependent samples have been developed that can be employed with ordinal data. Among the more commonly cited alternative procedures are the following: a) Marascuilo and McSweeney (1977) describe the extension of the **van der Waerden normal-scores test for k independent samples (Test 23)** (Van der Waerden (1953/1953) to a design involving k dependent samples. Conover (1980, 1999) notes that the normal-scores test developed by Bell and Doksum (1965) can also be extended to the latter design; b) **Page's test for ordered alternatives** (Page (1963)) can be employed with k dependent samples to evaluate an ordered alternative hypothesis. Specifically, in stating the alternative hypothesis, the ordinal position of the treatment effects is stipulated (as opposed to just stating that a difference exists between at least two of the k experimental conditions). **Page's test for ordered alternatives** is described in Daniel (1990), Marascuilo and McSweeney (1977), and Siegel and Castellan (1988); and c) Additional tests that can be employed with a k dependent samples design are either discussed or referenced in Conover (1980, 1999), Daniel (1990), Hollander and Wolfe (1999), Marascuilo and McSweeney (1977), and Sheskin (1984).

5. Relationship between the Friedman two-way analysis of variance by ranks and Kendall's coefficient of concordance The **Friedman two-way analysis of variance by ranks** and **Kendall's coefficient of concordance (Test 31)** (which is one of a number of measures of association that are described in this book) are based on the same statistical model. The latter measure of association is employed with three or more sets of ranks when rankings are based on

the **Friedman test** protocol. A full discussion of the relationship between the **Friedman two-way analysis of variance by ranks** and **Kendall's coefficient of concordance** (which can be used as a measure of effect size for the **Friedman test**) can be found in Section VII of **Kendall's coefficient of concordance**. When there are $n = 2$ subjects/sets of matched subjects, **Spearman's rank-order correlation coefficient (Test 29)**, which is linearly related to **Kendall's coefficient of concordance**, can be conceptualized within the framework of the **Friedman test** model. The latter relationship is discussed in Section VII of **Spearman's rank-order correlation coefficient**.

VIII. Additional Examples Illustrating the Use of the Friedman Two-Way Analysis of Variance by Ranks

The **Friedman two-way analysis of variance by ranks** can be employed to evaluate any of the additional examples noted for the **single-factor within-subjects analysis of variance**, if the data for the latter examples are rank-ordered. In addition, the **Friedman test** can be used to evaluate the data for any of the additional examples noted for the ***t* test for two dependent samples/binomial sign test for two dependent samples/Wilcoxon matched-pairs signed-ranks test**. Example 25.2 is an additional example that can be evaluated with the **Friedman two-way analysis of variance by ranks**. In Example 25.2 there is no need to rank-order interval/ratio data, since the results of the study are summarized in a rank-order format.¹⁵

Example 25.2 *Six horses are rank-ordered by a trainer with respect to their racing form on three different surfaces. Specifically, Track A has a cement surface, Track B a clay surface, and Track C a grass surface. Except for the surface, the three tracks are comparable to one another in all other respects. Table 25.4 summarizes the rankings of the horses on the three tracks. (In the case of Horse 6, the rank of 1.5 for both the clay and grass tracks reflects the fact that the horse was perceived to have equal form on both surfaces.) Do the data indicate that the form of a horse is related to the surface on which it is racing?*

Table 25.4 Data for Example 25.2

	Track A (Cement)	Track B (Clay)	Track C (Grass)
Horse 1	3	2	1
Horse 2	3	2	1
Horse 3	3	2	1
Horse 4	3	2	1
Horse 5	3	2	1
Horse 6	3	1.5	1.5

Since the ranks employed in Example 25.2 are identical to those employed for Example 25.1, the **Friedman test** will yield the identical result. Since most people would probably be inclined to employ a rank of 1 to represent a horse's best surface and a rank of 3 to represent a horse's worst surface, using such a ranking protocol, the track with the lowest sum of ranks (Track C) is associated with the best racing form and the track with the highest sum of ranks (Track A) is associated with the worst racing form.

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Endnotes

1. The reader should take note of the fact that when there are $k = 2$ dependent samples, the **Wilcoxon matched-pairs signed-ranks test** (which is also described in this book as a nonparametric test for evaluating ordinal data) will not yield a result equivalent to that obtained with the **Friedman two-way analysis of variance by ranks**. Since the **Wilcoxon test** (which rank-orders interval/ratio difference scores) employs more information than the **Friedman test/binomial sign test**, it provides a more powerful test of an alternative hypothesis than the latter tests.
2. A more detailed discussion of the guidelines noted below can be found in Sections I and VII of the ***t* test for two dependent samples**.
3. Although it is possible to conduct a directional analysis, such an analysis will not be

described with respect to the **Friedman two-way analysis of variance by ranks**. A discussion of a directional analysis when $k = 2$ can be found under the **binomial sign test for two dependent samples**. A discussion of the evaluation of a directional alternative hypothesis when $k \geq 3$ can be found in Section VII of the **chi-square goodness-of-fit test (Test 8)**. Although the latter discussion is in reference to analysis of a k independent samples design involving categorical data, the general principles regarding analysis of a directional alternative hypothesis when $k \geq 3$ are applicable to the **Friedman two-way analysis of variance by ranks**.

4. Note that this ranking protocol differs from that employed for other rank-order procedures discussed in the book. In other rank-order tests, the rank assigned to each score is based on the rank-order of the score within the overall distribution of $nk = N$ scores.
5. As noted in Section IV, the chi-square distribution provides an approximation of the **Friedman test** statistic. Although the chi-square distribution provides an excellent approximation of the Friedman sampling distribution, some sources recommend the use of exact probabilities for small sample sizes. Exact tables of the Friedman distribution are discussed in Section VII.
6. In the discussion of comparisons in reference to the analysis of variance, it is noted that a **simple** (also known as a **pairwise**) **comparison** is a comparison between any two groups/conditions in a set of k groups/conditions.
7. An alternative form of the comparison equation, which identifies the minimum required difference between the **means of the ranks** of any two conditions in order for them to differ from one another at the prespecified level of significance, is noted below.

$$CD_{F_{(\bar{R}_a - \bar{R}_b)}} = z_{\text{adj}} \sqrt{\frac{k(k + 1)}{6n}}$$

If the CD_F value computed with Equation 25.5 is divided by n , it yields the value $CD_{F_{(\bar{R}_a - \bar{R}_b)}}$ computed with the above equation.

8. The method for deriving the value of z_{adj} for the **Friedman two-way analysis of variance by ranks** is based on the same logic that is employed in Equation 22.5 (which is used for conducting comparisons for the **Kruskal-Wallis one-way analysis of variance by ranks**). A rationale for the use of the proportions .0167 and .0083 in determining the appropriate value for z_{adj} in Example 25.1 can be found in Endnote 5 of the **Kruskal-Wallis one-way analysis of variance by ranks**.
9. It should be noted that when a directional alternative hypothesis is employed, the sign of the difference between the two sums of ranks must be consistent with the prediction stated in the directional alternative hypothesis. When a nondirectional alternative hypothesis is employed, the direction of the difference between two sums of ranks is irrelevant.
10. In the case of both the **Wilcoxon matched-pairs signed-ranks test** and the **binomial sign test for two dependent samples**, it is assumed that for each pairwise comparison a subject's score in the second condition that is listed for a comparison is subtracted from the subject's

score in the first condition that is listed for the comparison. In the case of both tests, reversing the order of subtraction will yield the same result.

11. The value $n = 6$ is employed for the Condition 1 versus Condition 2 and Condition 1 versus Condition 3 comparisons, since no subject has the same score in both experimental conditions. On the other hand, the value $n = 5$ is employed in the Condition 2 versus Condition 3 comparison, since Subject 6 has the same score in Conditions 2 and 3. The use of $n = 5$ is predicated on the fact that in conducting the **Wilcoxon matched-pairs signed-ranks test**, subjects who have a difference score of zero are not included in the computation of the test statistic.
12. In Equation 25.5 the value $z_{.05} = 1.96$ is employed for z_{adj} , and the latter value is multiplied by 3.46, which is the value computed for the term in the radical of the equation for Example 25.1.
13. It is also the case that the exact binomial probability for the **binomial sign test for two dependent samples** will correspond to the exact probability for the **Friedman test statistic**.
14. If Subject 2 is included in the analysis, Equation 25.1 yields the value $\chi_r^2 = 4.9$ which is also significant at the .05 level.
15. In Section I it is noted that in employing the **Friedman test** it is assumed that the variable which is ranked is a continuous random variable. Thus, it would be assumed that the racing form of a horse was at some point either explicitly or implicitly expressed as a continuous interval/ratio variable.

Test 26

The Cochran Q Test (Nonparametric Test Employed with Categorical/Nominal Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Hypothesis evaluated with test In a set of k dependent samples (where $k \geq 2$), do at least two of the samples represent different populations?

Relevant background information on test It is recommended that before reading the material on the **Cochran Q test**, the reader review the general information on a dependent samples design contained in Sections I and VII of the **t test for two dependent samples (Test 17)**. The **Cochran Q test** (Cochran (1950)) is a nonparametric procedure for categorical data employed in a hypothesis testing situation involving a design with $k = 2$ or more dependent samples. The test is employed to evaluate an experiment in which a sample of n subjects (or n sets of matched subjects) is evaluated on a dichotomous dependent variable (i.e., scores on the dependent variable must fall within one of two mutually exclusive categories). The test assumes that each of the n subjects (or n sets of matched subjects) contributes k scores on the dependent variable. The **Cochran Q test** is an extension of the **McNemar test (Test 20)** to a design involving more than two dependent samples, and when $k = 2$ the **Cochran Q test** will yield a result that is equivalent to that obtained with the **McNemar test**. If the result of the **Cochran Q test** is significant, it indicates there is a high likelihood at least two of the k experimental conditions represent different populations.

The **Cochran Q test** is based on the following assumptions: a) The sample of n subjects has been randomly selected from the population it represents; and b) The scores of subjects are in the form of a dichotomous categorical measure involving two mutually exclusive categories.

Although the chi-square distribution is generally employed to evaluate the **Cochran test** statistic, in actuality the latter distribution is used to provide an approximation of the exact sampling distribution. Sources on nonparametric analysis (e.g., Daniel (1990), Marascuilo and McSweeney (1977), and Siegel and Castellan (1988)) recommend that for small sample sizes exact tables of the Q distribution derived by Patil (1975) be employed. Use of exact tables is generally recommended when $n < 4$ and/or $nk < 24$.

As is the case for other tests that are employed to evaluate data involving two or more dependent samples, in order for the **Cochran Q test** to generate valid results the following guidelines should be adhered to:¹ a) To control for order effects, the presentation of the k experimental conditions should be random or, if appropriate, be counterbalanced; and b) If matched samples are employed, within each set of matched subjects each of the subjects should be randomly assigned to one of the k experimental conditions.

As is noted with respect to other tests that are employed to evaluate a design involving two or more dependent samples, the **Cochran Q test** can also be used to evaluate a **before–after design**, as well as extensions of the latter design that involve more than two measurement periods. The limitations of the **before–after design** (which are discussed in Section VII of the **t test for two dependent samples**) are also applicable when it is evaluated with the **Cochran Q test**.

II. Example

Example 26.1 A market researcher asks 12 female subjects whether or not they would purchase an automobile manufactured by three different companies. Specifically, subjects are asked whether they would purchase a car manufactured by the following automobile manufacturers: Chenesco, Howasaki, and Gemini. The responses of the 12 subjects follow: **Subject 1** said she would purchase a Chenesco and a Howasaki but not a Gemini; **Subject 2** said she would only purchase a Howasaki; **Subject 3** said she would purchase all three makes of cars; **Subject 4** said she would only purchase a Howasaki; **Subject 5** said she would only purchase a Howasaki; **Subject 6** said she would purchase a Howasaki and a Gemini but not a Chenesco; **Subject 7** said she would not purchase any of the automobiles; **Subject 8** said she would only purchase a Howasaki; **Subject 9** said she would purchase a Chenesco and a Howasaki but not a Gemini; **Subject 10** said she would only purchase a Howasaki; **Subject 11** said she would not purchase any of the automobiles; and **Subject 12** said she would only purchase a Gemini. Can the market researcher conclude that there are differences with respect to car preference based on the responses of subjects?

III. Null versus Alternative Hypotheses

In stating the null and alternative hypotheses the notation π_j will be employed to represent the proportion of **Yes** responses in the population represented by the j^{th} experimental condition. Stated more generally, π_j represents the proportion of responses in one of the two response categories in the population represented by the j^{th} experimental condition.

Null hypothesis

$$H_0: \pi_1 = \pi_2 = \pi_3$$

(The proportion of **Yes** responses in the population represented by Condition 1 equals the proportion of **Yes** responses in the population represented by Condition 2 equals the proportion of **Yes** responses in the population represented by Condition 3.)

Alternative hypothesis

$$H_1: \text{Not } H_0$$

(This indicates that in at least two of the underlying populations represented by the $k = 3$ conditions, the proportion of **Yes** responses are not equal. It is important to note that the alternative hypothesis should not be written as follows: $H_1: \pi_1 \neq \pi_2 \neq \pi_3$. The reason why the latter notation for the alternative hypothesis is incorrect is because it implies that all three population proportions must differ from one another in order to reject the null hypothesis. In this book it will be assumed (unless stated otherwise) that the alternative hypothesis for the **Cochran Q test** is stated **nondirectionally**.)²

IV. Test Computations

The data for Example 26.1 are summarized in [Table 26.1](#). The number of subjects employed in the experiment is $n = 12$, and thus within each condition there are $n = n_1 = n_2 = n_3 = 12$ scores. The values **1** and **0** are employed to represent the two response categories in which a subject's response/categorization may fall. Specifically, a score of **1** indicates a **Yes** response and a score of **0** indicates a **No** response.

The following summary values are computed in [Table 26.1](#) which will be employed in the analysis of the data:

- a) The value $\sum C_j$ represents the number of **Yes** responses in the j^{th} condition. Thus, the

number of **Yes** responses in Conditions 1, 2, and 3 are, respectively, $\Sigma C_1 = 3$, $\Sigma C_2 = 9$, and $\Sigma C_3 = 3$.

b) The value $(\Sigma C_j)^2$ represents the square of the ΣC_j value computed for the j^{th} condition. The sum of the $k = 3$ $(\Sigma C_j)^2$ scores can be represented by the notation $\Sigma(\Sigma C_j)^2$. Thus, for Example 26.1, $\Sigma(\Sigma C_j)^2 = (\Sigma C_1)^2 + (\Sigma C_2)^2 + (\Sigma C_3)^2 = 9 + 81 + 9 = 99$.

c) The value R_i represents the sum of the $k = 3$ scores of the i^{th} subject (i.e., the number of **Yes** responses for the i^{th} subject). Note that an R_i value is computed for each of the $n = 12$ subjects. The sum of the n R_i scores is ΣR_i . Thus, for Example 26.1, $\Sigma R_i = 2 + 1 + \dots + 0 + 1 = 15$.

d) The value R_i^2 represents the square of the R_i score of the i^{th} subject. The sum of the n R_i^2 scores is ΣR_i^2 . Thus, for Example 26.1, $\Sigma R_i^2 = 4 + 1 + \dots + 0 + 1 = 27$.

e) The value p_j represents the proportion of **Yes** responses in the j^{th} condition. The value of p_j is computed as follows: $p_j = \Sigma C_j / n_j$. Thus, in Table 26.1 the values of p_j for Conditions 1, 2, and 3 are, respectively, $p_1 = .25$, $p_2 = .75$, and $p_3 = .25$.

Table 26.1 Data for Example 26.1

	Chenesco C_1	Howasaki C_2	Gemini C_3	R_i	R_i^2
Subject 1	1	1	0	2	4
Subject 2	0	1	0	1	1
Subject 3	1	1	1	3	9
Subject 4	0	1	0	1	1
Subject 5	0	1	0	1	1
Subject 6	0	1	1	2	4
Subject 7	0	0	0	0	0
Subject 8	0	1	0	1	1
Subject 9	1	1	0	2	4
Subject 10	0	1	0	1	1
Subject 11	0	0	0	0	0
Subject 12	0	0	1	1	1
	$\Sigma C_1 = 3$	$\Sigma C_2 = 9$	$\Sigma C_3 = 3$	$\Sigma R_i = 15$	$\Sigma R_i^2 = 27$
	$(\Sigma C_1)^2 = (3)^2 = 9$	$(\Sigma C_2)^2 = (9)^2 = 81$	$(\Sigma C_3)^2 = (3)^2 = 9$		
	$p_1 = \frac{\Sigma C_1}{n_1} = \frac{3}{12} = .25$	$p_2 = \frac{\Sigma C_2}{n_2} = \frac{9}{12} = .75$	$p_3 = \frac{\Sigma C_3}{n_3} = \frac{3}{12} = .25$		

Equation 26.1 is employed to calculate the test statistic for the **Cochran Q test**. The Q value computed with Equation 26.1 is interpreted as a chi-square value. In Equation 26.1 the following notation is employed with respect to the summary values noted in this section: a) C is employed to represent the value computed for $\Sigma(\Sigma C_j)^2$; b) T is employed to represent the value computed for ΣR_i ; and c) R is employed to represent the value computed for ΣR_i^2 . Thus, for Example 26.1, $C = 99$, $T = 15$, and $R = 27$.³

$$Q = \frac{(k - 1)[(k)(C) - (T)^2]}{(k)(T) - R} \quad \text{(Equation 26.1)}$$

Substituting the appropriate values from Example 26.1 in Equation 26.1, the value $Q = 8$ is computed.⁴

$$Q = \frac{(3 - 1)[(3)(99) - (15)^2]}{(3)(15) - 27} = 8$$

V. Interpretation of the Test Results

In order to reject the null hypothesis, the computed value $Q = \chi^2$ must be equal to or greater than the tabled critical chi-square value at the prespecified level of significance. The computed chi-square value is evaluated with **Table A4 (Table of the Chi-Square Distribution)** in the **Appendix**. For the appropriate degrees of freedom, the tabled $\chi^2_{.95}$ value (which is the chi-square value at the 95th percentile) and the tabled $\chi^2_{.99}$ value (which is the chi-square value at the 99th percentile) are employed as the .05 and .01 critical values for evaluating a nondirectional alternative hypothesis. The number of degrees of freedom employed in the analysis are computed with Equation 26.2. Thus, $df = 3 - 1 = 2$.

$$df = k - 1 \quad \text{(Equation 26.2)}$$

For $df = 2$, the tabled critical .05 and .01 chi-square values are $\chi^2_{.05} = 5.99$ and $\chi^2_{.01} = 9.21$. Since the computed value $Q = 8$ is greater than $\chi^2_{.05} = 5.99$, the alternative hypothesis is supported at the .05 level. Since, however, $Q = 8$ is less than $\chi^2_{.01} = 9.21$, the alternative hypothesis is not supported at the .01 level. A summary of the analysis of Example 26.1 with the **Cochran C test** follows: It can be concluded that there is a significant difference in subjects' preferences for at least two of the three automobiles. This result can be summarized as follows: $Q(2) = 8$, $p < .05$.

VI. Additional Analytical Procedures for the Cochran Q Test and/or Related Tests

1. Pairwise comparisons following computation of the test statistic for the Cochran Q test

Prior to reading this section the reader should review the discussion of comparisons in Section VI of the **single-factor between-subjects analysis of variance (Test 21)**. As is the case with the omnibus F value computed for an analysis of variance, the Q value computed with Equation 26.1 is based on an evaluation of all k experimental conditions. When the value of Q is significant, it does not indicate whether just two or, in fact, more than two conditions differ significantly from one another. In order to answer the latter question, it is necessary to conduct comparisons contrasting specific conditions with one another. This section will describe methodologies that can be employed for conducting **simple/pairwise comparisons** following the computation of a Q value.⁵

In conducting a simple comparison, the null hypothesis and nondirectional alternative hypothesis are as follows: $H_0: \pi_a = \pi_b$ versus $H_1: \pi_a \neq \pi_b$. In the aforementioned hypotheses, π_a and π_b represent the proportion of **Yes** responses in the populations represented by the two conditions involved in the comparison. The alternative hypothesis can also be stated directionally as follows: $H_1: \pi_a > \pi_b$ or $H_1: \pi_a < \pi_b$.

A number of sources (e.g., Fleiss (1981) and Marascuilo and McSweeney (1977)) describe comparison procedures for the **Cochran Q test**. The procedure to be described in this section, which is one of two procedures described in Marascuilo and McSweeney (1977), is essentially the application of the **Bonferroni–Dunn method** described in Section VI of the **single-factor between-subjects analysis of variance** to the **Cochran Q test** model. Through use of Equation 26.3, the procedure allows a researcher to identify the minimum required difference between the observed proportion of **Yes** responses for any two experimental conditions (designated as CD_C) in order for them to differ from one another at the prespecified level of significance.

$$CD_C = z_{adj} \sqrt{2 \left[\frac{(k)(T) - R}{(n^2)(k)(k - 1)} \right]} \quad (\text{Equation 26.3})$$

The value of z_{adj} is obtained from **Table A1 (Table of the Normal Distribution)** in the **Appendix**. In the case of a nondirectional alternative hypothesis, z_{adj} is the z value above which a proportion of cases corresponding to the value $\alpha_{FW}/2c$ falls (where c is the total number of comparisons that are conducted). In the case of a directional alternative hypothesis, z_{adj} is the z value above which a proportion of cases corresponding to the value α_{FW}/c falls. When all possible pairwise comparisons are made $c = [k(k - 1)]/2$, and thus, $2c = k(k - 1)$. In Example 26.1 the number of pairwise/simple comparisons that can be conducted is $c = [3(3 - 1)]/2 = 3$ — specifically, Condition 1 versus Condition 2, Condition 1 versus Condition 3, and Condition 2 versus Condition 3.

The value of z_{adj} will be a function of both the maximum **familywise Type I error rate** (α_{FW}) the researcher is willing to tolerate and the total number of comparisons that are conducted. When a limited number of comparisons are planned prior to collecting the data, most sources take the position that a researcher is not obliged to control the value of α_{FW} . In such a case, the **per comparison Type I error rate** (α_{PC}) will be equal to the prespecified value of alpha. When α_{FW} is not adjusted, the value of z_{adj} employed in Equation 26.3 will be the tabled critical z value that corresponds to the prespecified level of significance. Thus, if a nondirectional alternative hypothesis is employed and $\alpha = \alpha_{PC} = .05$, the tabled critical two-tailed .05 value $z_{.05} = 1.96$ is used to represent z_{adj} in Equation 26.3. If $\alpha = \alpha_{PC} = .01$, the tabled critical two-tailed .01 value $z_{.01} = 2.58$ is used in Equation 26.3. In the same respect, if a directional alternative hypothesis is employed, the tabled critical .05 and .01 one-tailed values $z_{.05} = 1.65$ and $z_{.01} = 2.33$ are used for z_{adj} in Equation 26.3.

When comparisons are not planned beforehand, it is generally acknowledged that the value of α_{FW} must be controlled so as not to become excessive. The general approach for controlling the latter value is to establish a **per comparison Type I error rate** which insures that α_{FW} will not exceed some maximum value stipulated by the researcher. One method for doing this (described under the **single-factor between-subjects analysis of variance** as the **Bonferroni–Dunn method**) establishes the **per comparison Type I error rate** by dividing the maximum value one will tolerate for the **familywise Type I error rate** by the total number of comparisons conducted. Thus, in Example 26.1, if one intends to conduct all three pairwise comparisons and wants to insure that α_{FW} does not exceed .05, $\alpha_{PC} = \alpha_{FW}/c = .05/3 = .0167$. The latter proportion is used in determining the value of z_{adj} . As noted earlier, if a directional alternative hypothesis is employed for a comparison, the value of z_{adj} employed in Equation 26.3 is the z value above which a proportion equal to $\alpha_{PC} = \alpha_{FW}/c$ of the cases falls. In **Table A1**, the z value that corresponds to the proportion .0167 is $z = 2.13$. By employing z_{adj} in Equation 26.3, one can be assured that within the “family” of three pairwise comparisons, α_{FW} will not exceed .05 (assuming all of the comparisons are directional). If a nondirectional alternative hypothesis is employed for all of the comparisons, the value of z_{adj} will be the z value above which a proportion equal to $\alpha_{FW}/2c = \alpha_{PC}/2$ of the cases falls. Since $\alpha_{PC}/2 = .0167/2 = .0083$, $z = 2.39$. By employing z_{adj} in Equation 26.3, one can be assured that α_{FW} will not exceed .05.⁶

Table 26.2 Difference Scores Between Pairs of Proportions for Example 26.1

$ p_1 - p_2 = .25 - .75 = .50$	$ p_1 - p_3 = .25 - .25 = 0$	$ p_2 - p_3 = .75 - .25 = .50$
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In order to employ the CD_C value computed with Equation 26.3, it is necessary to determine the absolute value of the difference between the proportion of **Yes** responses for each pair of experimental conditions that are compared.⁷ Table 26.2 summarizes the difference scores between pairs of proportions.

If any of the differences between two proportions is equal to or greater than the CD_C value computed with Equation 26.3, a comparison is declared significant. Equation 26.3 will now be employed to evaluate the nondirectional alternative hypothesis $H_1: \pi_a \neq \pi_b$ for all three pairwise comparisons. Since it will be assumed that the comparisons are unplanned and that the researcher does not want the value of α_{FW} to exceed .05, the value $z_{adj} = 2.39$ will be used in computing CD_C .

$$CD_C = (2.39) \sqrt{2 \left[\frac{(3)(15) - 27}{(12)^2(3)(3 - 1)} \right]} = (2.39)(.204) = .49$$

The obtained value $CD_C = .49$ indicates that any difference between a pair of proportions that is equal to or greater than .49 is significant. With respect to the three pairwise comparisons, the difference between Condition 1 and Condition 2 (which equals .50) and the difference between Condition 2 and Condition 3 (which also equals .50) are significant, since they are both greater than $CD_C = .49$. We cannot conclude that the difference between Condition 1 and Condition 3 is significant, since $|p_1 - p_3| = 0$ is less than $CD_C = .49$.

An alternative strategy that can be employed for conducting pairwise comparisons for the **Cochran Q test** is to use the **McNemar test** for each comparison. In employing the **McNemar test** one can employ either the chi-square or normal approximation of the test statistic for each comparison (the continuity-corrected value generally providing a more accurate estimate for a small sample size), or compute the exact binomial probability for the comparison. It will be demonstrated in Section VII, that the computed chi-square value computed with Equation 20.1 for the **McNemar test** yields the same $Q = \chi^2$ value that is obtained if a **Cochran Q test** (Equation 26.1) is employed to compare the same set of experimental conditions. In this section the exact binomial probabilities for the three pairwise comparisons for the **McNemar test** model will be computed. In order to compute the exact binomial probabilities (or, for that matter, the chi-square or normal approximations of the test statistic), the data for each comparison must be placed within a 2×2 table like Table 20.1 (which is the table for the **McNemar test** model). To illustrate this, the data for the Condition 1 versus Condition 2 comparison are recorded in Table 26.3. Note that of the $n = 12$ subjects involved in the comparison, only 6 of the subjects' scores are actually taken into account in computing the test statistic, since the other 6 subjects have the same score in both conditions.

Employing Table A6 (Table of the Binomial Distribution, Individual Probabilities) in the Appendix to compute the binomial probability, we determine that when $n = 6$, $P(x = 6) = .0156$. Thus, the two-tailed binomial probability for the Condition 1 versus Condition 2 comparison is $(2)(.0156) = .0312$. In the case of the Condition 1 versus Condition 3 comparison, the frequencies for Cells a , b , c , and d are, respectively, 1, 2, 2, and 7. Since the frequency of both Cells b and c is 2 (and thus, $n = 4$), the Condition 1 versus Condition 3 comparison results in no difference. In the case of the Condition 2 versus Condition 3 comparison, the frequencies for Cells a , b , c , and d are, respectively, 2, 1, 7, and 2. For the latter comparison, since $n = 8$, the frequencies for Cells b and c are 1 and 7. Using Table A6 (or Table A7 which is the Table of the Binomial Distribution, Cumulative Probabilities), we determine that when $n = 8$, $P(x \geq 7) = .0352$. Thus, the two-tailed binomial probability for the Condition 2 versus Condition 3 comparison is $(2)(.0352) = .0704$. Note that the binomial probabilities computed for the

Table 26.3 McNemar Test Model for Binomial Analysis of Condition 1 Versus Condition 2 Comparison

		Condition 1		Row sums
		Yes (1)	No (0)	
Condition 2	Yes (1)	$a = 3$	$b = 6$	9
	No (0)	$c = 0$	$d = 3$	3
Column sums		3	9	12

Condition 1 versus Condition 2 and Condition 2 versus Condition 3 comparisons are not identical, since by virtue of eliminating subjects who respond in the same category in both conditions from the analysis, the two comparisons employ different values for n (which is the sum of the frequencies for Cells b and c).

As before, if we wish to evaluate a nondirectional alternative hypothesis and insure that α_{FW} does not exceed .05, the value of α_{PC} is set equal to .0167. Thus, in order to reject the null hypothesis the computed two-tailed binomial probability for a comparison must be equal to or less than .0167. Since the computed two-tailed probabilities .0312 (for the Condition 1 versus Condition 2 comparison) and .0704 (for the Condition 2 versus Condition 3 comparison) are greater than .0167, none of the pairwise comparisons is significant.

In the event the researcher elects not to control the value of α_{FW} and employs $\alpha_{PC} = .05$ in evaluating the three pairwise comparisons (once again assuming a nondirectional analysis), only the Condition 1 versus Condition 2 comparison is significant, since the computed two-tailed binomial probability .0312 is less than .05. The Condition 2 versus Condition 3 comparison falls short of significance, since the computed two-tailed binomial probability .0704 is greater than .05. It should be noted that both of the aforementioned comparisons are significant if the directional alternative hypothesis that is consistent with the data is employed (since the one-tailed probabilities .0156 and .0352 are less than .05). If Equation 26.3 is employed for the same set of comparisons, $CD_C = (1.96)(.204) = .40$.⁸ Thus, employing the latter equation, the Condition 1 versus Condition 2 and Condition 2 versus Condition 3 comparisons are significant, since in both instances the difference between the two proportions is greater than $CD_C = .40$.

Although the binomial probabilities for the **McNemar test** for the Condition 1 versus Condition 2 and Condition 2 versus Condition 3 comparisons are larger than the probabilities associated with the use of Equation 26.3, both comparison procedures yield relatively low probability values for the two aforementioned comparisons. Thus, in the case of Example 26.1, depending upon which comparison procedure one employs (as well as the value of α_{PC} and whether one evaluates a nondirectional or directional alternative hypothesis) it would appear that there is a high likelihood that the Condition 1 versus Condition 2 and Condition 2 versus Condition 3 comparisons are significant. The intent of presenting two different comparison procedures in this section is to illustrate that, generally speaking, the results obtained with different procedures will be reasonably consistent with one another.⁹ As is noted in the discussion of comparisons in Section VI of the **single-factor between-subjects analysis of variance**, in instances where two or more comparison procedures yield inconsistent results, the most effective way to clarify the status of the null hypothesis is to replicate a study one or more times. It is also noted throughout the book that, in the final analysis, the decision regarding which of the available comparison procedures to employ is usually not the most important issue facing the researcher conducting comparisons. The main issue is what maximum value one is willing to tolerate for α_{FW} .

Marascuilo and McSweeney (1977) discuss the computation of a confidence interval for a comparison for the **Cochran Q test** model. One approach for computing a confidence interval

is to add to and subtract the computed value of CD_C from the obtained difference between the proportions involved in the comparison. The latter approach is based on the same logic employed for computing a confidence interval for a comparison in Section VI of the **single-factor between-subjects analysis of variance**.

VII. Additional Discussion of the Cochran Q Test

1. Issues relating to subjects who obtain the same score under all of the experimental conditions

a) Cochran (1950) noted that since the value computed for Q is not affected by the scores of any subject (or any row, if matched subjects are employed) who obtains either all 0s or all 1s in each of the experimental conditions, the scores of such subjects can be deleted from the data analysis. If the latter is done with respect to Example 26.1, the data for Subjects 3, 7, and 11 can be eliminated from the analysis (since Subjects 7 and 11 obtain all 0s, and Subject 3 obtains all 1s). It is demonstrated below that if the scores of Subjects 3, 7, and 11 are eliminated from the analysis, the value $Q = 8$ is still obtained when the revised summary values are substituted in Equation 26.1.

$$\Sigma C_1 = 2 \quad \Sigma C_2 = 8 \quad \Sigma C_3 = 2 \quad (\Sigma C_1)^2 = 4 \quad (\Sigma C_2)^2 = 64 \quad (\Sigma C_3)^2 = 4$$

$$\Sigma (\Sigma C_j)^2 = 4 + 64 + 4 = 72 \quad \Sigma R_i = 12 \quad \Sigma R_i^2 = 18$$

$$\text{Thus: } C = 72 \quad T = 12 \quad R = 18$$

$$Q = \frac{(3 - 1)[(3)(72) - (12)^2]}{(3)(12) - 18} = 8$$

It is noted in Section VI of the **McNemar test** that the latter test essentially eliminates from the analysis any subject who obtains the same score under both experimental conditions, and that this represents a limitation of the test. What was said with regard to the **McNemar test** in this respect also applies to the **Cochran Q test**. Thus, it is entirely possible to obtain a significant Q value even if the overwhelming majority of the subjects in a sample obtain the same score in each of the experimental conditions. To illustrate this, the value $Q = 8$ (obtained for Example 26.1) can be obtained for a sample of 1009 subjects, if 1000 of the subjects obtained a score of 1 in all three experimental conditions, and the remaining nine subjects had the same scores as Subjects 1, 2, 4, 5, 6, 8, 9, 10, and 12 in Example 26.1. Since the computation of the Q value in such an instance will be based on a sample size of 9 rather than on the actual sample size of 1009, it is reasonable to assume that such a result, although statistically significant, will not be of any practical significance from the perspective of the three automobile manufacturers. The latter statement is based on the fact that since all but 9 of the 1009 subjects said they would buy all three automobiles, there really does not appear to be any differences in preference that will be of any economic consequence to the manufacturers.

b) In Section I it is noted that when $n < 4$ and/or $nk < 24$, it is recommended that tables for the exact **Cochran test** statistic (derived by Patil (1975)) be employed instead of the chi-square approximation. In making such a determination, the value of n that should be used should not include any subjects who obtain all 0s or all 1s in each of the experimental conditions. Thus, in Example 26.1, the value $n = 9$ is employed, and not the value $n = 12$. Consequently $nk = (9)(3) = 27$. Since $n > 4$ and $nk > 24$, it is acceptable to employ the chi-square approximation.

c) Note that Equation 26.3 (the equation employed for conducting comparisons) employs the value of n for the total number of subjects, irrespective of whether a subject obtains the same

score in all k experimental conditions. The use of the latter n value maximizes the power of the comparison procedure. Certainly one could make an argument for employing as n in Equation 26.3 the number of subjects who have at least two different scores in the k experimental conditions. In most instances, the latter n value will be less than the total number of subjects employed in an experiment, and, subsequently, if the smaller n value is employed in Equation 26.3, the comparison procedure will be more conservative (since it will result in a higher value for CD_C).

2. Equivalency of the Cochran Q test and the McNemar test when $k = 2$ In Section I it is noted that when $k = 2$ the **Cochran Q test** yields a result that is equivalent to that obtained with the **McNemar test**. To be more specific, the **Cochran Q test** will yield a result that is equivalent to the **McNemar test** statistic when the correction for continuity is not employed for the latter test (i.e., the result obtained with Equation 20.1). In order to demonstrate the equivalency of the two tests, Example 26.2 will be evaluated with both tests.

Example 26.2 *A market researcher asks 10 female subjects whether or not they would purchase an automobile manufactured by two different companies. Specifically, subjects are asked whether they would purchase an automobile manufactured by Chenesco and Howasaki. Except for Subjects 2 and 3, all of the subjects said they would purchase a Chenesco but would not purchase a Howasaki. Subject 2 said she would not purchase either car, while Subject 3 said she would purchase a Howasaki but not a Chenesco. Based on the responses of subjects, can the market researcher conclude that there are differences with respect to car preference?*

Tables 26.4 and 26.5 respectively summarize the data for the study within the framework of the **Cochran Q test** model and the **McNemar test** model.

Table 26.4 Summary of Data for Analysis of Example 26.2 with Cochran Q Test

	Chenesco C_1	Howasaki C_2	R_i	R_i^2
Subject 1	1	0	1	1
Subject 2	0	0	0	0
Subject 3	0	1	1	1
Subject 4	1	0	1	1
Subject 5	1	0	1	1
Subject 6	1	0	1	1
Subject 7	1	0	1	1
Subject 8	1	0	1	1
Subject 9	1	0	1	1
Subject 10	1	0	1	1
	$\Sigma C_1 = 8$	$\Sigma C_2 = 1$	$\Sigma C_3 = 9$	$\Sigma R_i = 9$

Table 26.5 Summary of Data for Analysis of Example 26.2 with McNemar Test

		Condition 1 (Chenesco)		Row sums
		No (0)	Yes (1)	
Condition 2 (Howasaki)	No (0)	$a = 1$	$b = 8$	9
	Yes (1)	$c = 1$	$d = 0$	1
Column sums		2	8	10

Example 26.2 is evaluated below employing both the **Cochran Q test** and the **McNemar test**. Note the computed value $Q = \chi^2 = 5.44$ is equivalent to $\chi^2 = 5.44$ computed for the **McNemar test**.

Cochran Q test:

$$\Sigma C_1 = 8 \quad \Sigma C_2 = 1 \quad (\Sigma C_1)^2 = 64 \quad (\Sigma C_2)^2 = 1$$

$$\Sigma (\Sigma C_j)^2 = 64 + 1 = 65 \quad \Sigma R_i = 9 \quad \Sigma R_i^2 = 9$$

$$\text{Thus: } C = 65 \quad T = 9 \quad R = 9$$

$$Q = \frac{(2 - 1)[(2)(65) - (9)^2]}{(2)(9) - 9} = 5.44$$

McNemar test:

$$\chi^2 = \frac{(b - c)^2}{(b + c)} = \frac{(8 - 1)^2}{(8 + 1)} = 5.44$$

In the case of both tests, $df = 1$ (since in the case of the **Cochran Q test** $df = k - 1 = 2 - 1 = 1 = 2 - 1 = 1$, and in the case of the **McNemar test** the number of degrees of freedom is always $df = 1$). The tabled critical .05 and .01 chi-square values for $df = 1$ are $\chi_{.05}^2 = 3.84$ and $\chi_{.01}^2 = 6.63$. Since the obtained value $\chi^2 = 5.44$ is greater than $\chi_{.05}^2 = 3.84$, the nondirectional alternative hypothesis is supported at the .05 level. Since $\chi^2 = 5.44$ is less than $\chi_{.01}^2 = 6.63$, it is not supported at the .01 level.

In point of fact, the data in [Table 26.4](#) are based on Example 19.1, which is employed to illustrate the **binomial sign test for two dependent samples (Test 19)**. If we assume that in the case of Example 19.1 a subject is assigned a score of **1** in the condition in which she has a higher score and a score of **0** in the condition in which she has a lower score, plus the fact that a subject is assigned a score of **0** (or **1**) in both conditions if she has the same score, the data in [Table 19.1](#) will be identical to that presented in [Table 26.4](#).¹⁰ When Equation 19.3 (the uncorrected (for continuity) normal approximation for the **binomial sign test for two dependent samples**) is employed to evaluate Example 19.1, it yields the value $z = 2.33$ which, if squared, equals the obtained chi-square value for Example 26.2 — i.e., $(z = 2.33)^2 = (\chi^2 = 5.44)$.¹¹ Thus, when $k = 2$ the **McNemar test/Cochran Q test** are equivalent to the **binomial sign test for two dependent samples**. It should also be noted that the exact binomial probability computed for the **binomial sign test for two dependent samples** will be equivalent to the exact binomial probability computed when the **McNemar test/Cochran Q test** is employed to evaluate the same data. For Examples 19.1/26.2, the two-tailed binomial probability is $P(x \geq 8) = (2)(.0196) = .0392$ (for $n = 9$).

3. Alternative nonparametric procedures for categorical data for evaluating a design involving k dependent samples Daniel (1990) and/or Fliess (1981) note that alternative procedures for comparing k or more matched samples have been developed by Bennett (1967, 1968) and Shah and Claypool (1985). Chou (1989) describes a median test that can be employed to evaluate more than two dependent samples. The latter test, which employs the chi-square distribution to approximate the exact sampling distribution, employs subject/block medians as reference points in determining whether two or more of the treatment conditions represent different populations. The test described by Chou (1989) assumes that subjects' original scores are in an interval/ratio format and are converted into categorical data.

VIII. Additional Examples Illustrating the Use of the Cochran Q Test

Since the **Cochran Q test** can be employed to evaluate any dependent samples design involving two or more experimental conditions, it can also be used to evaluate any of the examples discussed under the **McNemar test**. Examples 26.3–26.7 are additional examples that can be evaluated with the **Cochran Q test**. Examples 26.6 and 26.7 represent extensions of a **before–after design** to a design involving $k = 3$ experimental conditions. Since the data for all of the examples in this section (with the exception of Example 26.7) are identical to the data employed in Example 26.1, they yield the same result.

Example 26.3 *A researcher wants to assess the relative likelihood of three brands of house paint fading within two years of application. In order to make this assessment he applies the following three brands of house paint that are identical in hue to a sample of houses that have cedar shingles: Brightglow, Colorfast, and Prismalong. In selecting the houses the researcher identifies 12 neighborhoods which vary with respect to geographical conditions, and within each neighborhood he randomly selects 3 houses. Within each block of three houses, one of the houses is painted with Brightglow, a second house with Colorfast, and a third house with Prismalong. Thus, a total of 36 houses are painted in the study. Two years after the houses are painted, an independent judge categorizes each house with respect to whether or not the paint on its shingles has faded. A house is assigned the number 1 if there is evidence of fading and the number 0 if there is no evidence of fading. Table 26.6 summarizes the results of the study. Do the data indicate differences between the three brands of house paint with respect to fading?*

Table 26.6 Data for Example 26.3

	Brand of paint		
	Brightglow	Colorfast	Prismalong
Block 1	1	1	0
Block 2	0	1	0
Block 3	1	1	1
Block 4	0	1	0
Block 5	0	1	0
Block 6	0	1	1
Block 7	0	0	0
Block 8	0	1	0
Block 9	1	1	0
Block 10	0	1	0
Block 11	0	0	0
Block 12	0	0	1

Note that in Example 26.3 the 12 blocks, comprised of 3 houses per block, are analogous to the use of 12 sets of matched subjects with 3 subjects per set/block. The brands of house paint represent the three levels of the independent variable, and the judge’s categorization for each house with respect to fading (i.e., 1 versus 0) represents the dependent variable. Based on the analysis conducted for Example 26.1, there is a strong suggestion that Colorfast paint is perceived as more likely to fade than the other two brands.

Example 26.4 *Twelve male marines are administered a test of physical fitness which requires that an individual achieve the minimum criterion noted for the following three tasks: a) Climb a 100 ft. rope; b) Do 25 chin-ups; and c) Run a mile in under six minutes. Within the sample of*

12 subjects, the order of presentation of the three tasks is completely counterbalanced (i.e., each of the six possible presentation orders for the tasks is presented to two subjects). For each of the tasks a subject is assigned a score of **1** if he achieves the minimum criterion and a score of **0** if he does not. [Table 26.7](#) summarizes the results of the testing. Do the data indicate there is a difference between the three tasks with respect to subjects achieving the criterion?

Table 26.7 Data for Example 26.4

	Task		
	Rope climb	Chin-ups	Mile run
Subject 1	1	1	0
Subject 2	0	1	0
Subject 3	1	1	1
Subject 4	0	1	0
Subject 5	0	1	0
Subject 6	0	1	1
Subject 7	0	0	0
Subject 8	0	1	0
Subject 9	1	1	0
Subject 10	0	1	0
Subject 11	0	0	0
Subject 12	0	0	1

Based on the analysis conducted for Example 26.1, the data suggest that subjects are more likely to achieve the criterion for chin-ups than they are for the other two tasks.

Example 26.5 A horticulturist working at a university is hired to evaluate the effectiveness of three different kinds of weed killer (Zapon, Snuffout, and Shalom). Twelve athletic fields of equal size are selected as test sites. The researcher divides each athletic field into three equally sized areas, and within each field (based on random determination) he applies one kind of weed killer to one third of the field, a second kind of weed killer to another third of the field, and the third kind of weed killer to the remaining third of the field. This procedure is employed for all 12 athletic fields, resulting in 36 separate areas to which weed killer is applied. Six months after application of the weed killer, an independent judge evaluates the 36 areas with respect to weed growth. The judge employs the number **1** to indicate that an area has evidence of weed growth and the number **0** to indicate that an area does not have evidence of weed growth. [Table 26.8](#) summarizes the judge's categorizations. Do the data indicate there is a difference in the effectiveness between the three kinds of weed killer?

Note that in Example 26.5 the 12 athletic fields are analogous to 12 subjects who are evaluated under three experimental conditions. The three brands of weed killer represent the levels of the independent variable, and the judge's categorization of each area with respect to weed growth (i.e., **1** versus **0**) represents the dependent variable. Based on the analysis conducted for Example 26.1, the data suggest that Snuffout is less effective than the other two brands of weed killer.

Example 26.6 A social scientist conducts a study assessing the impact of a federal gun control law on rioting in large cities. Assume that as a result of legislative changes the law in question, which severely limits the public's access to firearms, was not in effect between the years 1985–1989, but was in effect during the five years directly preceding and following that time

period (i.e., the gun control law was in effect during the periods 1980–1984 and 1990–1994). In conducting the study, the social scientist categorizes 12 large cities with respect to whether or not there was a major riot within each of the three designated time periods. Thus, each city is categorized with respect to whether or not a riot occurred during: a) 1980–1984, during which time the gun control law was in effect (Time 1); b) 1985–1989, during which time the gun control law was not in effect (Time 2); and c) 1990–1994, during which time the gun control law was in effect (Time 3). A code of **1** is employed to indicate the occurrence of at least one major riot during a specified five-year time period, and a code of **0** is employed to indicate the absence of a major riot during a specified time period. Table 26.9 summarizes the results of the study. Do the data indicate the gun control law had an effect on rioting?

Table 26.8 Data for Example 26.5

	Weed killer		
	Zapon	Snuffout	Shalom
Field 1	1	1	0
Field 2	0	1	0
Field 3	1	1	1
Field 4	0	1	0
Field 5	0	1	0
Field 6	0	1	1
Field 7	0	0	0
Field 8	0	1	0
Field 9	1	1	0
Field 10	0	1	0
Field 11	0	0	0
Field 12	0	0	1

Table 26.9 Data for Example 26.6

	Time period		
	Time 1 (1980–1984)	Time 2 (1985–1989)	Time 3 (1990–1994)
New York	1	1	0
Chicago	0	1	0
Detroit	1	1	1
Philadelphia	0	1	0
Los Angeles	0	1	0
Dallas	0	1	1
Houston	0	0	0
Miami	0	1	0
Washington	1	1	0
Boston	0	1	0
Baltimore	0	0	0
Atlanta	0	0	1

Note that in Example 26.6 the 12 cities are analogous to 12 subjects who are evaluated during three time periods. Example 26.6 can be conceptualized as representing what is referred to as a **time series design**. A **time series design** is essentially a **before–after design** in which one or more blocks are evaluated one or more times both prior to and following an experimental treatment. In Example 26.6 each of the cities represents a block. **Time series** designs are most commonly employed in the social sciences when a researcher wants to evaluate social change through analysis of archival data (i.e., public records). The internal validity of a **time series**

design is limited insofar as the treatment is not manipulated by the researcher, and thus any observed differences across time periods with respect to the dependent variable may be due to extraneous variables over which the researcher has no control. Thus, although when Example 26.6 is evaluated with the **Cochran Q test** the obtained Q value is significant (suggesting that more riots occurred when the gun control law was not in effect), other circumstances (such as the economy, race relations, etc.) may have varied across time periods, and such factors (as opposed to the gun control law) may have been responsible for the observed effect.¹² Another limitation of the time series design described by Example 26.6 is that since the membership of the blocks is not the result of random assignment, the various blocks will not be directly comparable to one another.

In closing the discussion of Example 26.6, it should be noted that in practice the **Cochran Q test** is not commonly employed to evaluate a **time series design**. Additionally, it is worth noting that, in the final analysis, it is probably more prudent to conceptualize Example 26.6 as a **mixed factorial design**, viewing each of the cities as a separate level of a second independent variable. In a **mixed factorial design** involving two independent variables, one independent variable is a between-subjects variable (i.e., each subject/block is evaluated under only one level of that independent variable), while the other independent variable is a within-subjects variable (i.e., each subject/block is evaluated under all levels of that independent variable). If Example 26.6 is conceptualized as a **mixed factorial design**, the different cities represent the between-subjects variable and the three time periods represent the within-subjects variable. Such a design is typically evaluated with the **factorial analysis of variance for a mixed design (Test 27i)** which is discussed in Section IX (the **Addendum**) of the **between-subjects factorial analysis of variance (Test 27)**. It should be noted, however, that in employing the latter analysis of variance, the dependent variable is generally represented by interval/ratio level data.¹³

Example 26.7 *In order to assess the efficacy of a drug which a pharmaceutical company claims is effective in treating hyperactivity, 12 hyperactive children are evaluated during the following three time periods: a) One week prior to taking the drug; b) After a child has taken the drug for six consecutive months; and c) Six months after the drug is discontinued. The children are observed by judges who employ a standardized procedure for evaluating hyperactivity. The procedure requires that during each time period a child be assigned a score of 1 if he is hyperactive and a score of 0 if he is not hyperactive. During the evaluation process, the judges are blind with respect to whether a child is taking medication at the time he or she is evaluated. Table 26.10 summarizes the results of the study. Do the data indicate the drug is effective?*

Example 26.7 employs the same experimental design to evaluate the hypothesis that is evaluated in Example 24.7 (in Section VIII of the **single-factor within-subjects analysis of variance (Test 24)**). In Example 26.7, however, categorical data are employed to represent the dependent variable. Evaluation of the data with the **Cochran Q test** yields the value $Q = 14.89$.

$$\Sigma C_1 = 12 \quad \Sigma C_2 = 3 \quad \Sigma C_3 = 10 \quad (\Sigma C_1)^2 = 144 \quad (\Sigma C_2)^2 = 9 \quad (\Sigma C_3)^2 = 100$$

$$\Sigma (\Sigma C_j)^2 = 144 + 9 + 100 = 253 \quad \Sigma R_i = 25 \quad \Sigma R_i^2 = 57$$

$$\text{Thus: } C = 253 \quad T = 25 \quad R = 57$$

$$Q = \frac{(3 - 1)[(3)(253) - (25)^2]}{(3)(25) - 57} = 14.89$$

Table 26.10 Data for Example 26.7

	Time Period		
	Time 1	Time 2	Time 3
Child 1	1	0	1
Child 2	1	0	1
Child 3	1	0	1
Child 4	1	0	0
Child 5	1	0	0
Child 6	1	0	1
Child 7	1	1	1
Child 8	1	0	1
Child 9	1	0	1
Child 10	1	0	1
Child 11	1	1	1
Child 12	1	1	1

Since $k = 3$, $df = 2$. The tabled critical .05 and .01 values for $df = 2$ are $\chi^2_{.05} = 5.99$ and $\chi^2_{.01} = 9.21$. Since the obtained value $Q = \chi^2 = 14.89$ is greater than both of the aforementioned critical values, the alternative hypothesis is supported at both the .05 and .01 levels. Inspection of Table 26.10 strongly suggests that the significant effect is due to the lower frequency of hyperactivity during the time subjects are taking the drug (Time period 2). The latter, of course, can be confirmed by conducting comparisons between pairs of time periods.

As noted in the discussion of Example 24.7, the design of the latter study does not adequately control for the effects of extraneous/confounding variables. The same comments noted in the aforementioned discussion also apply to Example 26.7. Example 26.7 can also be conceptualized within the context of a time-series design.

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Endnotes

1. A more detailed discussion of the guidelines noted below can be found in Sections I and VII of the ***t* test for two dependent samples**.
2. Although it is possible to conduct a directional analysis, such an analysis will not be described with respect to the **Cochran *Q* test**. A discussion of a directional analysis when $k = 2$ can be found under the **McNemar test**. A discussion of the evaluation of a directional alternative hypothesis when $k \geq 3$ can be found in Section VII of the **chi-square goodness-of-fit test (Test 8)**. Although the latter discussion is in reference to analysis of a k independent samples design involving categorical data, the general principles regarding analysis of a directional alternative hypothesis when $k \geq 3$ are applicable to the **Cochran *Q* test**.
3. The use of Equation 26.1 to compute the **Cochran *Q* test** statistic assumes that the columns in the summary table (i.e., [Table 26.1](#)) are employed to represent the k levels of the independent variable, and that the rows are employed to represent the n subjects/matched sets of subjects. If the columns and rows are reversed (i.e., the columns are employed to represent the subjects/matched sets of subjects, and the rows the levels of the independent variable), Equation 26.1 cannot be employed to compute the value of Q .
4. The same Q value is obtained if the frequencies of **No** responses (**0**) are employed in computing the summary values used in Equation 26.1 instead of the frequencies of **Yes** (**1**) responses. To illustrate this, the data for Example 26.1 are evaluated employing the frequencies of **No** (**0**) responses.

$$\Sigma C_1 = 9 \quad \Sigma C_2 = 3 \quad \Sigma C_3 = 9 \quad (\Sigma C_1)^2 = 81 \quad (\Sigma C_2)^2 = 9 \quad (\Sigma C_3)^2 = 81$$

$$\Sigma (\Sigma C_j)^2 = 81 + 9 + 81 = 171 \quad \Sigma R_i = 21 \quad \Sigma R_i^2 = 45$$

$$\text{Thus: } C = 171 \quad T = 21 \quad R = 45$$

$$Q = \frac{(3 - 1)[(3)(171) - (21)^2]}{(3)(21) - 45} = 8$$

5. In the discussion of comparisons in reference to the analysis of variance, it is noted that a **simple** (also known as a **pairwise**) **comparison** is a comparison between any two groups/conditions in a set of k groups/conditions.
6. The method for deriving the value of z_{adj} for the **Cochran *Q* test** is based on the same logic that is employed in Equation 22.5 (which is used for conducting comparisons for the **Kruskal–Wallis one-way analysis of variance by ranks (Test 22)**). A rationale for the

use of the proportions .0167 and .0083 in determining the appropriate value for z_{adj} in Example 26.1 can be found in Endnote 5 of the **Kruskal–Wallis one-way analysis of variance by ranks**.

7. It should be noted that when a directional alternative hypothesis is employed, the sign of the difference between the two proportions must be consistent with the prediction stated in the directional alternative hypothesis. When a nondirectional alternative hypothesis is employed, the direction of the difference between the two proportions is irrelevant.
8. In Equation 26.3 the value $z_{.05} = 1.96$ is employed for z_{adj} , and the latter value is multiplied by .204, which is the value computed for the term in the radical of the equation for Example 26.1.
9. In point of fact, Equation 26.3 employs more information than the **McNemar test**, and thus provides a more powerful test of an alternative hypothesis than the latter test (assuming both tests employ the same value for α_{PC}). The lower power of the **McNemar test** is directly attributed to the fact that for a given comparison, it only employs the scores of those subjects who obtain different scores under the two experimental conditions.
10. In conducting the **binomial sign test for two dependent samples**, what is relevant is in which of the two conditions a subject has a higher score, which is commensurate with assigning a subject to one of two response categories. As is the case with the **McNemar test** and the **Cochran Q test**, the analysis for the **binomial sign test for two dependent samples** does not include subjects who obtain the same score in both conditions.
11. The value $\chi^2 = 5.44$ is also obtained for Example 19.1 through use of Equation 8.2, which is the equation for the **chi-square goodness-of-fit test**. In the case of Example 19.1 the latter equation produces an equivalent result to that obtained with Equation 19.3 (the normal approximation). The result of the binomial analysis of Example 19.1 with the **chi-square goodness-of-fit test** is summarized in [Table 19.2](#).
12. Within the framework of a time series design, one or more blocks can be included which can serve as controls. Specifically, in Example 26.6 additional cities might have been selected in which the gun control law was always in effect (i.e., in effect during Time 2 as well as during Times 1 and 3). Differences on the dependent variable during Time 2 between the control cities and the cities in which the law was nullified between 1985–1989 could be contrasted to further evaluate the impact of the gun control law. Unfortunately, if the law in question is national, such control cities would not be available in the nation in which the study is conducted. The reader should note, however, that even if such control cities were available, the internal validity of such a study would still be subject to challenge, since it would still not ensure adequate control over extraneous variables.
13. Related to the issue of employing an analysis of variance with a design such as that described by Example 26.6, Cochran (1950) and Winer *et al.* (1991) note that if a **single-factor within-subjects analysis of variance** is employed to evaluate the data in the **Cochran Q test** summary table (i.e., [Table 26.1](#)), it generally leads to similar conclusions as those reached when the data are evaluated with Equation 26.1. The question of whether it is appropriate to employ an analysis of variance to evaluate the categorical data in the **Cochran Q test** summary table is an issue on which researchers do not agree.

**Inferential Statistical Test Employed
with Factorial Design
(and Related Measures of
Association/Correlation)**

Test 27: [The Between-Subjects Factorial Analysis of Variance](#)

Test 27

The Between-Subjects Factorial Analysis of Variance (Parametric Test Employed with Interval/Ratio Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

The **between-subjects factorial analysis of variance** is one of a number of analysis of variance procedures that are employed to evaluate a **factorial design**. A factorial design is employed to simultaneously evaluate the effect of two or more independent variables on a dependent variable. Each of the independent variables is referred to as a **factor**. Each of the factors has two or more levels, which refer to the number of groups/experimental conditions that comprise that independent variable. If a factorial design is not employed to assess the effect of multiple independent variables on a dependent variable, separate experiments must be conducted to evaluate the effect of each of the independent variables. One major advantage of a factorial design is that it allows the same set of hypotheses to be evaluated at a comparable level of power by using only a fraction of the subjects that would be required if separate experiments were conducted to evaluate the relevant hypotheses for each of the independent variables. Another advantage of a factorial design is that it permits a researcher to evaluate whether or not there is an **interaction** between two or more independent variables — the latter being something that cannot be determined if only one independent variable is employed in a study. An **interaction** is present in a set of data when the performance of subjects on one independent variable is not consistent across all the levels of another independent variable. The concept of interaction is discussed in detail in Section V.

The **between-subjects factorial analysis of variance** (also known as a **completely randomized factorial analysis of variance**) is an extension of the **single-factor between-subjects analysis of variance** (Test 21) to experiments involving two or more independent variables. Although the **between-subjects factorial analysis of variance** can be used for more than two factors, the computational procedures described in this book will be limited to designs involving two factors. One of the factors will be designated by the letter **A**, and will have p levels, and the second factor will be designated by the letter **B**, and will have q levels. As a result of this, there will be a total of $p \times q$ groups. A $p \times q$ **between-subjects/completely randomized factorial design** requires that each of the $p \times q$ groups is comprised of different subjects who have been randomly assigned to that group. Each group serves under one of the p levels of Factor A and one of the q levels of Factor B, with no two groups serving under the same combination of levels of the two factors. All possible combinations of the levels of Factor A and Factor B are represented by the total $p \times q$ groups.

The **between-subjects factorial analysis of variance** evaluates the following hypotheses:

a) With respect to Factor A: In the set of p independent samples (where $p \geq 2$), do at least two of the samples represent populations with different mean values? The latter hypothesis can also be stated as follows: Do at least two of the levels of Factor A represent populations with different mean values?

b) With respect to Factor B: In the set of q independent samples (where $q \geq 2$), do at least two of the samples represent populations with different mean values? The latter hypothesis can

also be stated as follows: Do at least two of the levels of Factor B represent populations with different mean values?

c) In addition to evaluating the above hypotheses (which assess the presence or absence of what are referred to as **main effects**),¹ the **between-subjects factorial analysis of variance** evaluates the hypothesis of whether there is a significant **interaction** between the two factors/independent variables.

A discussion of the theoretical rationale underlying the evaluation of the three sets of hypotheses for the **between-subjects factorial analysis of variance** can be found in Section VII.

The **between-subjects factorial analysis of variance** is employed with interval/ratio data and is based on the following assumptions: a) Each sample has been randomly selected from the population it represents; b) The distribution of data in the underlying population from which each of the samples is derived is normal; and c) The third assumption, which is referred to as the **homogeneity of variance** assumption, states that the variances of the $p \times q$ underlying populations represented by the $p \times q$ groups are equal to one another. The homogeneity of variance assumption (which is discussed earlier in the book in reference to the ***t* test for two independent samples (Test 11)**, the ***t* test for two dependent samples (Test 17)**, the **single-factor between-subjects analysis of variance** and the **single-factor within-subjects analysis of variance (Test 24)**) is discussed in greater detail in Section VI. If any of the aforementioned assumptions of the **between-subjects factorial analysis of variance** are saliently violated, the reliability of the computed test statistic may be compromised.

II. Example

Example 27.1 *A study is conducted to evaluate the effect of humidity (to be designated as Factor A) and temperature (to be designated as Factor B) on mechanical problem-solving ability. The experimenter employs a 2×3 between-subjects factorial design. The two levels that comprise Factor A are A_1 : Low humidity; A_2 : High humidity. The three levels that comprise Factor B are B_1 : Low temperature; B_2 : Moderate temperature; B_3 : High temperature. The study employs 18 subjects, each of whom is randomly assigned to one of the six experimental groups (i.e., $p \times q = 2 \times 3 = 6$) resulting in three subjects per group. Each of the six experimental groups represents a different combination of the levels that comprise the two factors. The number of mechanical problems solved by the three subjects in each of the six experimental conditions/groups follow. (The notation Group AB_{jk} indicates the group that served under Level j of Factor A and Level k of Factor B.) **Group AB_{11}** : Low humidity/Low temperature (11, 9, 10); **Group AB_{12}** : Low humidity/Moderate temperature (7, 8, 6); **Group AB_{13}** : Low humidity/High temperature (5, 4, 3); **Group AB_{21}** : High humidity/Low temperature (2, 4, 3); **Group AB_{22}** : High humidity/Moderate temperature (4, 5, 3); **Group AB_{23}** : High humidity/High temperature (0, 1, 2). Do the data indicate that either humidity or temperature influences mechanical problem-solving ability?*

III. Null versus Alternative Hypotheses

A **between-subjects factorial analysis of variance** involving two factors evaluates three sets of hypotheses. The first set of hypotheses evaluates the effect of Factor A on the dependent variable, the second set evaluates the effect of Factor B on the dependent variable, and the third set evaluates whether or not there is an interaction between the two factors.

Set 1: Hypotheses for Factor A

Null hypothesis

$$H_0: \mu_{A_1} = \mu_{A_2}$$

(The mean of the population Level 1 of Factor A represents equals the mean of the population Level 2 of Factor A represents.)

Alternative hypothesis

$$H_1: \mu_{A_1} \neq \mu_{A_2}$$

(The mean of the population Level 1 of Factor A represents does not equal the mean of the population Level 2 of Factor A represents. This is a nondirectional alternative hypothesis. In the discussion of the **between-subjects factorial analysis of variance** it will be assumed (unless stated otherwise) that an alternative hypothesis is stated **nondirectionally**.² In order for the alternative hypothesis for Factor A to be supported, the obtained F value for Factor A (designated by the notation F_A) must be equal to or greater than the tabled critical F value at the prespecified level of significance.)

Set 2: Hypotheses for Factor B

Null hypothesis

$$H_0: \mu_{B_1} = \mu_{B_2} = \mu_{B_3}$$

(The mean of the population Level 1 of Factor B represents equals the mean of the population Level 2 of Factor B represents equals the mean of the population Level 3 of Factor B represents.)

Alternative hypothesis

$$H_1: \text{Not } H_0$$

(This indicates that there is a difference between at least two of the $q = 3$ population means. It is important to note that the alternative hypothesis should not be written as follows: $H_1: \mu_{B_1} \neq \mu_{B_2} \neq \mu_{B_3}$. The reason why the latter notation for the alternative hypothesis is incorrect is because it implies that all three population means must differ from one another in order to reject the null hypothesis. In order for the alternative hypothesis for Factor B to be supported, the obtained F value for Factor B (designated by the notation F_B) must be equal to or greater than the tabled critical F value at the prespecified level of significance.)

Set 3: Hypotheses for interaction

$$H_0: \text{There is no interaction between Factor A and Factor B.}$$

$$H_1: \text{There is an interaction between Factor A and Factor B.}$$

Although it is possible to state the null and alternative hypotheses for the interaction symbolically, such a format will not be employed since it requires a considerable amount of notation. It should be noted that in predicting an interaction, a researcher may be very specific with respect to the pattern of the interaction that is predicted. As a general rule, however, such predictions are not reflected in the statement of the null and alternative hypotheses. In order for the alternative hypothesis for the interaction to be supported, the obtained F value for the interaction (designated by the notation F_{AB}) must be equal to or greater than the tabled critical F value at the prespecified level of significance.

IV. Test Computations

The test statistics for the **between-subjects factorial analysis of variance** can be computed with either **computational** or **definitional equations**. Although definitional equations reveal the underlying logic behind the analysis of variance, they involve considerably more calculations than do the computational equations. Because of the latter, computational equations will be employed in this section to demonstrate the computation of the test statistic. The definitional equations for the **between-subjects factorial analysis of variance** are described in Section VII.

The data for Example 27.1 are summarized in [Table 27.1](#). In the latter table the following notation is employed.

- N represents the total number of subjects who serve in the experiment. In Example 27.1, $N = 18$.
- ΣX_T represents the total sum of the scores of the $N = 18$ subjects who serve in the experiment.
- \bar{X}_T represents the mean of the scores of the $N = 18$ subjects who serve in the experiment. \bar{X}_T will be referred to as the **grand mean**.
- ΣX_T^2 represents the total sum of the squared scores of the $N = 18$ subjects who serve in the experiment.
- $(\Sigma X_T)^2$ represents the square of the total sum of scores of the $N = 18$ subjects who serve in the experiment.
- $n_{AB_{jk}}$ represents the number of subjects who serve in Group AB_{jk} . In Example 27.1 $n_{AB_{jk}} = 3$. In some of the equations that follow, the notation n is employed to represent the value $n_{AB_{jk}}$.
- $\Sigma X_{AB_{jk}}$ represents the sum of the scores of the $n_{AB_{jk}} = 3$ subjects who serve in Group AB_{jk} .
- $\bar{X}_{AB_{jk}}$ represents the mean of the scores of the $n_{AB_{jk}} = 3$ subjects who serve in Group AB_{jk} .
- $\Sigma X_{AB_{jk}}^2$ represents the sum of the squared scores of the $n_{AB_{jk}} = 3$ subjects who serve in Group AB_{jk} .
- $(\Sigma X_{AB_{jk}})^2$ represents the square of the sum of scores of the $n_{AB_{jk}} = 3$ subjects who serve in Group AB_{jk} .
- n_{A_j} represents the number of subjects who serve in level j of Factor A. In Example 27.1, $n_{A_j} = (n_{AB_{jk}})(q) = (3)(3) = 9$.
- ΣX_{A_j} represents the sum of the scores of the $n_{A_j} = 9$ subjects who serve in Level j of Factor A.
- \bar{X}_{A_j} represents the mean of the scores of the $n_{A_j} = 9$ subjects who serve in level j of Factor A.
- $\Sigma X_{A_j}^2$ represents the sum of the squared scores of the $n_{A_j} = 9$ subjects who serve in Level j of Factor A.
- $(\Sigma X_{A_j})^2$ represents the square of the sum of scores of the $n_{A_j} = 9$ subjects who serve in Level j of Factor A.
- n_{B_k} represents the number of subjects who serve in level k of Factor B. In Example 27.1, $n_{B_k} = (n_{AB_{jk}})(p) = (3)(2) = 6$.
- ΣX_{B_k} represents the sum of the scores of the $n_{B_k} = 6$ subjects who serve in Level k of Factor B.
- \bar{X}_{B_k} represents the mean of the scores of the $n_{B_k} = 6$ subjects who serve in Level k of Factor B.
- $\Sigma X_{B_k}^2$ represents the sum of the squared scores of the $n_{B_k} = 6$ subjects who serve in Level k of Factor B.

$(\sum X_{B_k})^2$ represents the square of the sum of scores of the $n_{B_k} = 6$ subjects who serve in Level k of Factor B.

Table 27.1 Data for Example 27.1

Factor A (Humidity)	Factor B (Temperature)			
	B_1 (Low)	B_2 (Moderate)	B_3 (High)	Row sums
A_1 (Low)	Group AB_{11}	Group AB_{12}	Group AB_{13}	Level A_1
	$X_{AB_{11}}$ $X_{AB_{11}}^2$	$X_{AB_{12}}$ $X_{AB_{12}}^2$	$X_{AB_{13}}$ $X_{AB_{13}}^2$	
	11 121	7 49	5 25	
	9 81	8 64	4 16	
	10 100	6 36	3 9	
	$n_{AB_{11}} = 3$ $\sum X_{AB_{11}} = 30$ $\bar{X}_{AB_{11}} = \frac{\sum X_{AB_{11}}}{n_{AB_{11}}} = \frac{30}{3} = 10$ $\sum X_{AB_{11}}^2 = 302$ $(\sum X_{AB_{11}})^2 = (30)^2 = 900$	$n_{AB_{12}} = 3$ $\sum X_{AB_{12}} = 21$ $\bar{X}_{AB_{12}} = \frac{\sum X_{AB_{12}}}{n_{AB_{12}}} = \frac{21}{3} = 7$ $\sum X_{AB_{12}}^2 = 149$ $(\sum X_{AB_{12}})^2 = (21)^2 = 441$	$n_{AB_{13}} = 3$ $\sum X_{AB_{13}} = 12$ $\bar{X}_{AB_{13}} = \frac{\sum X_{AB_{13}}}{n_{AB_{13}}} = \frac{12}{3} = 4$ $\sum X_{AB_{13}}^2 = 50$ $(\sum X_{AB_{13}})^2 = (12)^2 = 144$	$n_{A_1} = 9$ $\sum X_{A_1} = 63$ $\bar{X}_{A_1} = \frac{\sum X_{A_1}}{n_{A_1}} = \frac{63}{9} = 7$ $\sum X_{A_1}^2 = 501$ $(\sum X_{A_1})^2 = (63)^2 = 3969$
A_2 (High)	Group AB_{21}	Group AB_{22}	Group AB_{23}	Level A_2
	$X_{AB_{21}}$ $X_{AB_{21}}^2$	$X_{AB_{22}}$ $X_{AB_{22}}^2$	$X_{AB_{23}}$ $X_{AB_{23}}^2$	
	2 4	4 16	0 0	
	4 16	5 25	1 1	
	3 9	3 9	2 4	
	$n_{AB_{21}} = 3$ $\sum X_{AB_{21}} = 9$ $\bar{X}_{AB_{21}} = \frac{\sum X_{AB_{21}}}{n_{AB_{21}}} = \frac{9}{3} = 3$ $\sum X_{AB_{21}}^2 = 29$ $(\sum X_{AB_{21}})^2 = (9)^2 = 81$	$n_{AB_{22}} = 3$ $\sum X_{AB_{22}} = 12$ $\bar{X}_{AB_{22}} = \frac{\sum X_{AB_{22}}}{n_{AB_{22}}} = \frac{12}{3} = 4$ $\sum X_{AB_{22}}^2 = 50$ $(\sum X_{AB_{22}})^2 = (12)^2 = 144$	$n_{AB_{23}} = 3$ $\sum X_{AB_{23}} = 3$ $\bar{X}_{AB_{23}} = \frac{\sum X_{AB_{23}}}{n_{AB_{23}}} = \frac{3}{3} = 1$ $\sum X_{AB_{23}}^2 = 5$ $(\sum X_{AB_{23}})^2 = (3)^2 = 9$	$n_{A_2} = 9$ $\sum X_{A_2} = 24$ $\bar{X}_{A_2} = \frac{\sum X_{A_2}}{n_{A_2}} = \frac{24}{9} = 2.67$ $\sum X_{A_2}^2 = 84$ $(\sum X_{A_2})^2 = (24)^2 = 576$
Column sums	Level B_1	Level B_2	Level B_3	Grand Total
	$n_{B_1} = 6$	$n_{B_2} = 6$	$n_{B_3} = 6$	$N = 18$
	$\sum X_{B_1} = 39$	$\sum X_{B_2} = 33$	$\sum X_{B_3} = 15$	$\sum X_T = 87$
	$\bar{X}_{B_1} = \frac{\sum X_{B_1}}{n_{B_1}} = \frac{39}{6} = 6.5$	$\bar{X}_{B_2} = \frac{\sum X_{B_2}}{n_{B_2}} = \frac{33}{6} = 5.5$	$\bar{X}_{B_3} = \frac{\sum X_{B_3}}{n_{B_3}} = \frac{15}{6} = 2.5$	$\bar{X}_T = \frac{\sum X_T}{N} = \frac{87}{18} = 4.83$
	$\sum X_{B_1}^2 = 331$	$\sum X_{B_2}^2 = 199$	$\sum X_{B_3}^2 = 55$	$\sum X_T^2 = 585$
	$(\sum X_{B_1})^2 = (39)^2 = 1521$	$(\sum X_{B_2})^2 = (33)^2 = 1089$	$(\sum X_{B_3})^2 = (15)^2 = 225$	$(\sum X_T)^2 = (87)^2 = 7569$

As is the case for the **single-factor between-subjects analysis of variance**, the total variability for the **between-subjects factorial analysis of variance** can be divided into **between-groups variability** and **within-groups variability**. The **between-groups variability** can be divided into the following: a) Variability attributable to Factor A; b) Variability attributable to Factor B; and c) Variability attributable to any interaction that is present between Factors A and B (which will be designated as AB variability). For each of the variability components involved in the **between-subjects factorial analysis of variance**, a sum of squares is computed. Thus, the following sum of squares values are computed: a) SS_T , the **total sum of squares**; b) SS_{BG} , the **between-groups sum of squares**; c) SS_A , the **sum of squares for Factor A** (which can also be referred to as the **row sum of squares**, since in Table 27.1 Factor A is the row variable); d) SS_B , the **sum of squares for Factor B** (which can also be referred to as the **column sum of squares**, since in Table 27.1 Factor B is the column variable); e) SS_{AB} , the **interaction sum of squares**; and f) SS_{WG} , the **within-groups sum of squares**, which is also referred to as the **error sum of squares** or **residual sum of squares**, since it represents variability that is due to chance factors which are beyond the control of the researcher. Each of the aforementioned sum of squares values represents the numerator in the equation that is employed to compute the variance for that variability component (which is referred to as the **mean square** for that component).

Equations 27.1–27.3 summarize the relationship between the sum of squares components for the **between-subjects factorial analysis of variance**. Equation 27.1 summarizes the relationship between the between-groups, the within-groups, and the total sums of squares.

$$SS_T = SS_{BG} + SS_{WG} \quad (\text{Equation 27.1})$$

Because of the relationship noted in Equation 27.2, Equation 27.1 can also be written in the form of Equation 27.3.

$$SS_{BG} = SS_A + SS_B + SS_{AB} \quad (\text{Equation 27.2})$$

$$SS_T = SS_A + SS_B + SS_{AB} + SS_{WG} \quad (\text{Equation 27.3})$$

In order to compute the sums of squares for the **between-subjects factorial analysis of variance**, the following summary values are computed with Equations 27.4–27.8 which will be employed as elements in the computational equations: $[XS]$, $[T]$, $[A]$, $[B]$, $[AB]$.³ The reader should take note of the fact that in the equations that follow, the following is true: a) $n_{AB_k} = n = 3$; b) $N = npq$, and thus, $N = (3)(2)(3) = 18$; c) $n_{A_j} = nq$, and thus, $n_{A_j} = (3)(3) = 9$; d) $n_{B_k} = np$, and thus, $n_{B_k} = (3)(2) = 6$.

The summary value $[XS] = 585$ is computed with Equation 27.4.

$$[XS] = \sum X_T^2 = (11)^2 + (9)^2 + (10)^2 + \cdots + (0)^2 + (1)^2 + (2)^2 = 585 \quad (\text{Equation 27.4})$$

The summary value $[T] = 420.5$ is computed with Equation 27.5.

$$[T] = \frac{(\sum X_T)^2}{N} = \frac{(87)^2}{18} = 420.5 \quad (\text{Equation 27.5})$$

The summary value $[A] = 505$ is computed with Equation 27.6.

$$[A] = \sum_{j=1}^p \left[\frac{(\sum X_{A_j})^2}{n_{A_j}} \right] = \frac{(63)^2}{9} + \frac{(24)^2}{9} = 505 \quad (\text{Equation 27.6})$$

The notation $\sum_{j=1}^p [(\sum X_{A_j})^2 / n_{A_j}]$ in Equation 27.6 indicates that for each level of Factor A, the scores of the $n_{A_j} = 9$ subjects who serve under that level of the factor are summed, the resulting value is squared, and the obtained value is divided by $n_{A_j} = 9$. The values obtained for each of the $p = 2$ levels of Factor A are then summed.

The summary value $[B] = 472.5$ is computed with Equation 27.7.

$$[B] = \sum_{k=1}^q \left[\frac{(\sum X_{B_k})^2}{n_{B_k}} \right] = \frac{(39)^2}{6} + \frac{(33)^2}{6} + \frac{(15)^2}{6} = 472.5 \quad (\text{Equation 27.7})$$

The notation $\sum_{k=1}^q [(\sum X_{B_k})^2 / n_{B_k}]$ in Equation 27.7 indicates that for each level of Factor B, the scores of the $n_{B_k} = 6$ subjects who serve under that level of the factor are summed, the resulting value is squared, and the obtained value is divided by $n_{B_k} = 6$. The values obtained for each of the $q = 3$ levels of Factor B are then summed.

The summary value $[AB] = 573$ is computed with Equation 27.8.

$$[AB] = \sum_{k=1}^q \sum_{j=1}^p \left[\frac{(\sum X_{AB_{jk}})^2}{n_{AB_{jk}}} \right] = \frac{(30)^2}{3} + \frac{(9)^2}{3} + \frac{(21)^2}{3} + \frac{(12)^2}{2} + \frac{(12)^2}{3} + \frac{(3)^2}{3} = 573 \quad (\text{Equation 27.8})$$

The notation $\sum_{k=1}^q \sum_{j=1}^p [(\sum X_{AB_{jk}})^2 / n_{AB_{jk}}]$ in Equation 27.8 indicates that for each of the $pq = 6$ groups, the scores of the $n_{AB_{jk}} = 3$ subjects who serve in that group are summed, the resulting value is squared, and the obtained value is divided by $n_{AB_{jk}} = 3$. The values obtained for each of the $pq = 6$ groups are then summed.

Employing the summary values computed with Equations 27.4–27.8, Equations 27.9–27.14 can be employed to compute the values SS_T , SS_{BG} , SS_A , SS_B , SS_{AB} , and SS_{WG} .

Equation 27.9 is employed to compute the value $SS_T = 164.5$.

$$SS_T = [XS] - [T] = 585 - 420.5 = 164.5 \quad (\text{Equation 27.9})$$

Equation 27.10 is employed to compute the value $SS_{BG} = 152.5$.

$$SS_{BG} = [AB] - [T] = 573 - 420.5 = 152.5 \quad (\text{Equation 27.10})$$

Equation 27.11 is employed to compute the value $SS_A = 84.5$.

$$SS_A = [A] - [T] = 505 - 420.5 = 84.5 \quad (\text{Equation 27.11})$$

Equation 27.12 is employed to compute the value $SS_B = 52$.

$$SS_B = [B] - [T] = 472.5 - 420.5 = 52 \quad (\text{Equation 27.12})$$

Equation 27.13 is employed to compute the value $SS_{AB} = 16$.

$$(\text{Equation 27.13})$$

$$SS_{AB} = [AB] - [A] - [B] + [T] = 573 - 505 - 472.5 + 420.5 = 16$$

Equation 27.14 is employed to compute the value $SS_{WG} = 12$.⁴

$$SS_{WG} = [XS] - [AB] = 585 - 573 = 12 \quad (\text{Equation 27.14})$$

Note that $SS_{BG} = SS_A + SS_B + SS_{AB} = 84.5 + 52 + 16 = 152.5$ and $SS_T = SS_{BG} + SS_{WG} = 152.5 + 12 = 164.5$.

The reader should take note of the fact that the values SS_T , SS_{BG} , SS_A , SS_B , SS_{AB} , and SS_{WG} must always be positive numbers. If a negative value is obtained for any of the aforementioned values, it indicates a computational error has been made.

At this point the **mean square** values (which as previously noted represent variances) for the above components can be computed. In order to compute the test statistics for the **between-subjects factorial analysis of variance**, it is only required that the following mean square values be computed: MS_A , MS_B , MS_{AB} , and MS_{WG} .

MS_A is computed with Equation 27.15.

$$MS_A = \frac{SS_A}{df_A} \quad (\text{Equation 27.15})$$

MS_B is computed with Equation 27.16.

$$MS_B = \frac{SS_B}{df_B} \quad (\text{Equation 27.16})$$

MS_{AB} is computed with Equation 27.17.

$$MS_{AB} = \frac{SS_{AB}}{df_{AB}} \quad (\text{Equation 27.17})$$

MS_{WG} is computed with Equation 27.18.

$$MS_{WG} = \frac{SS_{WG}}{df_{WG}} \quad (\text{Equation 27.18})$$

In order to compute MS_A , MS_B , MS_{AB} , and MS_{WG} , it is required that the values df_A , df_B , df_{AB} , and df_{WG} (the denominators of Equations 27.15–27.18) be computed. df_A are computed with Equation 27.19.

$$df_A = p - 1 \quad (\text{Equation 27.19})$$

df_B are computed with Equation 27.20.

$$df_B = q - 1 \quad (\text{Equation 27.20})$$

df_{AB} are computed with Equation 27.21.

$$df_{AB} = (p - 1)(q - 1) \quad (\text{Equation 27.21})$$

df_{WG} are computed with Equation 27.22. As noted earlier, the value n is equivalent to the value $n_{AB_{jk}}$. The use of n in any of the equations for the **between-subjects factorial analysis of variance** assumes that there are an equal number of subjects in each of the pq groups.

$$df_{WG} = pq(n - 1) \quad (\text{Equation 27.22})$$

Although they are not required in order to compute the F ratios for the **between-subjects factorial analysis of variance**, the **between-groups degrees of freedom** (df_{BG}), and the **total degrees of freedom** (df_T) are generally computed, since they can be used to confirm the df values computed with Equations 27.19–27.22, as well as the fact that they are employed in the analysis of variance summary table.

df_{BG} are computed with Equation 27.23.

$$df_{BG} = pq - 1 \quad (\text{Equation 27.23})$$

df_T are computed with Equation 27.24.

$$df_T = N - 1 \quad (\text{Equation 27.24})$$

The relationships between the various degrees of freedom values are described below.

$$df_{BG} = df_A + df_B + df_{AB} \quad df_T = df_{BG} + df_{WG}$$

Employing Equations 27.19–27.24, the values $df_A = 1$, $df_B = 2$, $df_{AB} = 2$, $df_{WG} = 12$, $df_{BG} = 5$, and $df_T = 17$ are computed.

$$\begin{aligned} df_A &= 2 - 1 = 1 & df_B &= 3 - 1 = 2 & df_{AB} &= (2 - 1)(3 - 1) = 2 \\ df_{WG} &= (2)(3)(3 - 1) = 12 & df_{BG} &= [(2)(3)] - 1 = 5 & df_T &= 18 - 1 = 17 \end{aligned}$$

Note that $df_{BG} = df_A + df_B + df_{AB} = 1 + 2 + 2 = 5$ and $df_T = df_{BG} + df_{WG} = 5 + 12 = 17$.

Employing Equations 27.15–27.18, the following values are computed: $MS_A = 84.5$, $MS_B = 26$, $MS_{AB} = 8$, $MS_{WG} = 1$.

$$MS_A = \frac{84.5}{1} = 84.5 \quad MS_B = \frac{52}{2} = 26 \quad MS_{AB} = \frac{16}{2} = 8 \quad MS_{WG} = \frac{12}{12} = 1$$

The F ratio is the test statistic for the **between-subjects factorial analysis of variance**. Since, however, there are three sets of hypotheses to be evaluated, it is required that three F ratios be computed — one for each of the components that comprise the between-groups variability. Specifically, an F ratio is computed for Factor A, for Factor B, and for the AB interaction. Equations 27.25–27.27 are, respectively, employed to compute the three F ratios.

$$F_A = \frac{MS_A}{MS_{WG}} \quad (\text{Equation 27.25})$$

$$F_B = \frac{MS_B}{MS_{WG}} \quad (\text{Equation 27.26})$$

$$F_{AB} = \frac{MS_{AB}}{MS_{WG}} \quad (\text{Equation 27.27})$$

Employing Equations 27.25–27.27, the values $F_A = 84.5$, $F_B = 26$, and $F_{AB} = 8$ are computed.

$$F_A = \frac{84.5}{1} = 84.5 \quad F_B = \frac{26}{1} = 26 \quad F_{AB} = \frac{8}{1} = 8$$

The reader should take note of the fact that any value computed for a mean square or an F ratio must always be a positive number. If a negative value is obtained for any mean square or F ratio, it indicates a computational error has been made. If $MS_{WG} = 0$, Equations 27.25–27.27 will be insoluble. The only time $MS_{WG} = 0$ is when, within each of the pq groups, all subjects obtain the same score (i.e., there is no within-groups variability). If the mean values for all of the levels of any factor are identical, the mean square value for that factor will equal zero, and, if the latter is true, the F value for that factor will also equal zero.

V. Interpretation of the Test Results

It is common practice to summarize the results of a **between-subjects factorial analysis of variance** with the summary table represented by [Table 27.2](#).

Table 27.2 Summary Table of Analysis of Variance for Example 27.1

Source of variation	<i>SS</i>	<i>df</i>	<i>MS</i>	<i>F</i>
Between-groups	152.5	5		
A	84.5	1	84.5	84.5
B	52	2	26	26
AB	16	2	8	8
Within-groups	12	12	1	
Total	164.5	17		

The obtained F values are evaluated with [Table A10 \(Table of the \$F\$ Distribution\)](#) in the [Appendix](#). In [Table A10](#) critical values are listed in reference to the number of degrees of freedom associated with the numerator and the denominator of an F ratio. Thus, in the case of Example 27.1 the values for df_A , df_B , and df_{AB} are employed for the numerator degrees of freedom for each of the three F ratios, while df_{WG} is employed as the denominator degrees of freedom for all three F ratios. As is the case in the discussion of other analysis of variance procedures discussed in the book, the notation $F_{.05}$ is employed to represent the tabled critical F value at the .05 level. The latter value corresponds to the tabled $F_{.95}$ value in [Table A10](#). In the same respect, the notation $F_{.01}$ will be employed to represent the tabled critical F value at the .01 level, and the latter value will correspond to the relevant tabled $F_{.99}$ value in [Table A10](#).

The following tabled critical values are employed in evaluating the three F ratios computed for Example 27.1: a) **Factor A**: For $df_{\text{num}} = df_A = 1$ and $df_{\text{den}} = df_{WG} = 12$, $F_{.05} = 4.75$ and $F_{.01} = 9.33$; b) **Factor B**: For $df_{\text{num}} = df_B = 2$ and $df_{\text{den}} = df_{WG} = 12$, $F_{.05} = 3.89$ and $F_{.01} = 6.93$; c) **AB interaction**: For $df_{\text{num}} = df_{AB} = 2$ and $df_{\text{den}} = df_{WG} = 12$, $F_{.05} = 3.89$ and $F_{.01} = 6.93$.

In order to reject the null hypothesis in reference to a computed F ratio, the obtained F value must be equal to or greater than the tabled critical value at the prespecified level of significance.

Since the computed value $F_A = 84.5$ is greater than $F_{.05} = 4.75$ and $F_{.01} = 9.33$, the alternative hypothesis for Factor A is supported at both the .05 and .01 levels. Since the computed value $F_B = 26$ is greater than $F_{.05} = 3.89$ and $F_{.01} = 6.93$, the alternative hypothesis for Factor B is supported at both the .05 and .01 levels. Since the computed value $F_{AB} = 8$ is greater than $F_{.05} = 3.89$ and $F_{.01} = 6.93$, the alternative hypothesis for an interaction between Factors A and B is supported at both the .05 and .01 levels. The aforementioned results can be summarized as follows: $F_A(1,12) = 84.5$, $p < .01$; $F_B(2,12) = 26$, $p < .01$; $F_{AB}(2,12) = 8$, $p < .01$.

The analysis of the data for Example 27.1 allows the researcher to conclude that both humidity (Factor A) and temperature (Factor B) have a significant impact on problem-solving scores. Thus, both main effects are significant. As previously noted, a main effect describes the effect of one factor/independent variable on the dependent variable, ignoring any effect any of the other factors/independent variables might have on the dependent variable. There is also, however, a significant interaction present in the data. As noted in Section I, the latter indicates that the effect of one factor is not consistent across all the levels of the other factor. It is important to note that the presence of an interaction renders any significant main effects meaningless, since it requires that the relationship described by a main effect be qualified. This is the case, since when an interaction is present, the nature of the relationship between the levels of a factor on which a significant main effect is detected will depend upon which level of the second factor is considered. Table 27.3, which summarizes the data for Example 27.1, will be used to illustrate this point. The six cells in the Table 27.3 contain the means of the $pq = 6$ groups. The values in the margins of the rows and columns of the table, respectively, represent the means of the levels of Factor A and Factor B. In Table 27.3 the average of any row or column can be obtained by adding all of the values in that row or column, and dividing the sum by the number of cells in that row or column.⁵

Table 27.3 Group and Marginal Means for Example 27.1

		Factor B (Temperature)			Row averages
		B_1 (Low)	B_2 (Moderate)	B_3 (High)	
Factor A (Humidity)	A_1 (Low)	10	7	4	7
	A_2 (High)	3	4	1	2.67
Column averages		6.5	5.5	2.5	Grand mean = 4.83

In Table 27.3 the main effect for Factor A (Humidity) indicates that as humidity increases the number of problems solved decreases (since $(\bar{X}_{A_1} = 7) > (\bar{X}_{A_2} = 2.67)$). Similarly, the main effect for Factor B (Temperature) indicates that as temperature increases, the number of problems solved decreases (since $(\bar{X}_{B_1} = 6.5) > (\bar{X}_{B_2} = 5.5) > (\bar{X}_{B_3} = 2.5)$). However, closer inspection of the data reveals that the effects of the factors on the dependent variable are not as straightforward as the main effects suggest. Specifically, the ordinal relationship depicted for the main effect on Factor B is only applicable to Level 1 of Factor A. Although under the low humidity condition (A_1) the number of problems solved decreases as temperature increases, the latter is not true for the high humidity condition (A_2). Under the latter condition the number of problems solved increases from 3 to 4 as temperature increases from low to moderate but then decreases to 1 under the high temperature condition. Thus, the main effect for Factor B is misleading, since it is based on the result of averaging the data from two rows which do not contain consistent patterns of information. In the same respect, if one examines the main effect on Factor A, it suggests that as humidity increases, performance decreases. Table 27.3, however, reveals

that although this ordinal relationship is observed for all three levels of Factor B, the effect is much more pronounced for Level 1 (low temperature) than it is for either Level 2 (moderate temperature) or Level 3 (high temperature). Thus, even though the ordinal relationship described by the main effect is consistent across the three levels of Factor B, the magnitude of the relationship varies depending upon which level of Factor B is considered.

Figure 27.1 summarizes the information presented in Table 27.3 in a graphical format. Each of the points depicted in the graphs described by Figures 27.1a and 27.1b represents the average score of the group that corresponds to the level of the factor represented by the line on which that point falls and the level of the factor on the abscissa (X-axis) above which the point falls. An interaction is revealed on either graph when two or more of the lines are not equidistant from one another throughout the full length of the graph, as one moves from left to right. When two or more lines on a graph intersect with one another, as is the case in Figure 27.1a, or two or more lines diverge from one another, as is the case in Figure 27.1b, it more than likely indicates the presence of an interaction. The ultimate determination, however, with respect to whether or not a significant interaction is present should always be based on the computed value of the F_{AB} ratio.

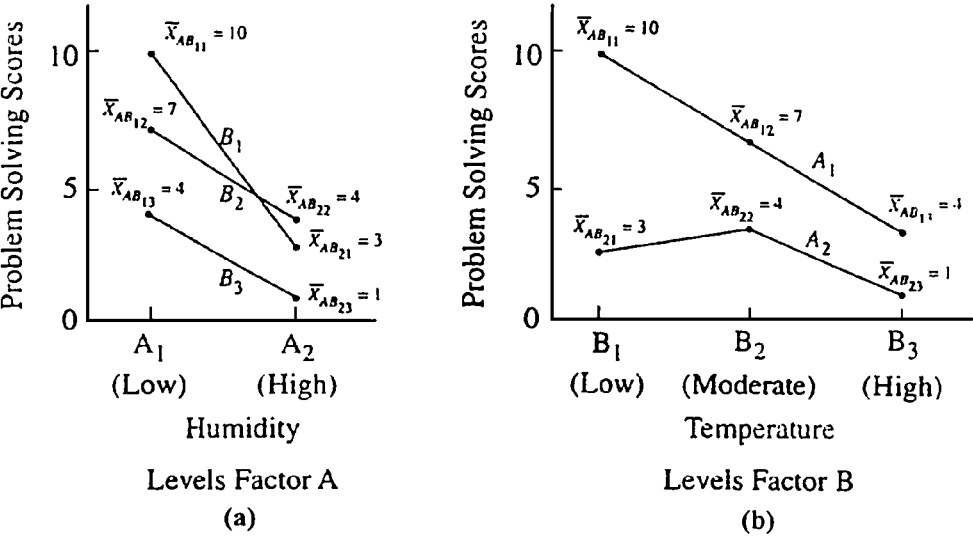


Figure 27.1 Graphical Summary of Results of Example 27.1

In an experiment in which there are two factors, either of two graphs can be employed to summarize the results of the study. In Figure 27.1a the levels of Factor A are represented on the abscissa, and three lines are employed to represent subjects' performance on each of the levels of Factor B (with reference to the specific levels of Factor A). In Figure 27.1b the levels of Factor B are represented on the abscissa, and two lines are employed to represent subjects' performance on each of the levels of Factor A (with reference to the specific levels of Factor B). As noted earlier, the fact that an interaction is present is reflected in Figures 27.1a and 27.1b, since the lines are not equidistant from one another throughout the length of both graphs.⁶

Table 27.4 and Figure 27.2 summarize a hypothetical set of data (for the same experiment described by Example 27.1) in which no interaction is present. For purposes of illustration it will be assumed that in this example the computed values F_A and F_B are significant, while F_{AB} is not.

Table 27.4 Hypothetical Values for Group and Marginal Means When There Is No Interaction

		Factor B (Temperature)			Row averages
		B_1 (Low)	B_2 (Moderate)	B_3 (High)	
Factor A (Humidity)	A_1 (Low)	10	8	6	8
	A_2 (High)	6	4	2	4
Column averages		8	6	4	Grand mean = 6

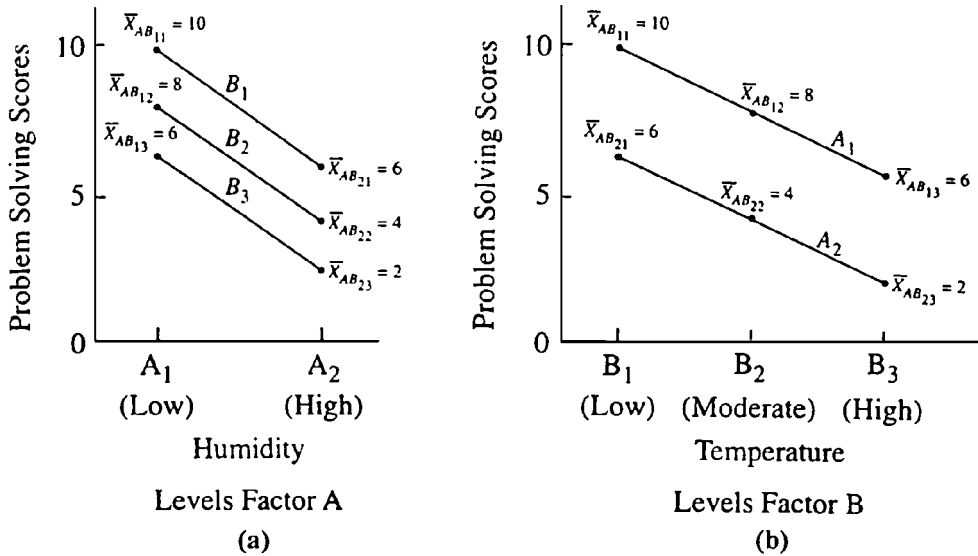


Figure 27.2 Graphical Summary of Results Described in Table 27.4

Inspection of Table 27.4 and Figure 27.2 indicates the presence of a main effect on both Factors A and B and the absence of an interaction. The presence of a main effect on Factor A is reflected in the fact that there is a reasonably large difference between $\bar{X}_{A_1} = 8$ and $\bar{X}_{A_2} = 4$. In the same respect, the significant main effect on Factor B is reflected in the discrepancy between the mean values $\bar{X}_{B_1} = 8$, $\bar{X}_{B_2} = 6$, and $\bar{X}_{B_3} = 4$. The conclusion that there is no interaction is based on the fact that the relationship described by each of the main effects is consistent across all of the levels of the second factor. To illustrate this, consider the main effect described for Factor A. In Table 27.4, the main effect for Factor A indicates that subjects solve 4 more problems under the low humidity condition than under the high humidity condition, and since this is the case regardless of which level of Factor B one considers, it indicates that there is no interaction between the two factors. The absence of an interaction is reflected in Figure 27.2a, since the three lines are equidistant from one another. In Table 27.4 the main effect for Factor B indicates that the number of problems solved decreases in steps of 2 as one progresses from low to moderate to high temperature. This pattern is consistent across both of the levels of Factor A. The absence of an interaction is also reflected in Figure 27.2b, since the two lines representing each of the levels of Factor A are equidistant from one another (as well as being parallel) throughout the length of the graph.

The term **additive model** is commonly employed to describe an analysis of variance in

which there is no interaction (whereas the term **nonadditive** is employed when there is an interaction). The use of the term **additive** within this context reflects the fact that the mean of any of the $p \times q$ cells can be obtained by adding the row and column effects for that cell to the grand mean (Myers and Well, 1995).

VI. Additional Analytical Procedures for the Between-Subjects Factorial Analysis of Variance and/or Related Tests

1. Comparisons following the computation of the F values for the between-subjects factorial analysis of variance Upon computing the omnibus F values, further analysis of the data comparing one or more groups and/or factor levels with one another can provide a researcher with more detailed information regarding the relationship between the independent variables and the dependent variable. Since the procedures to be described in this section are essentially extensions of those employed for the **single-factor between-subjects analysis of variance**, the reader should review the discussion of comparison procedures in Section VI of the latter test before proceeding. The discussion in this section will examine additional analytical procedures that can be conducted following the computation of the F values under the following three conditions: a) **No significant main effects or interaction are present**; b) **One or both main effects are significant, but the interaction is not significant**; and c) **A significant interaction is present, with or without one or more of the main effects being significant**. [Table 27.5](#) is a summary table for Example 27.1 depicting all of the group means for which comparison procedures will be described in this section.

Table 27.5 Summary Table of Means for Example 27.1

		Factor B (Temperature)			Row averages
		B_1	B_2	B_3	
Factor A (Humidity)	A_1	$\bar{X}_{AB_{11}}$	$\bar{X}_{AB_{12}}$	$\bar{X}_{AB_{13}}$	\bar{X}_{A_1}
	A_2	$\bar{X}_{AB_{21}}$	$\bar{X}_{AB_{22}}$	$\bar{X}_{AB_{23}}$	\bar{X}_{A_2}
Column averages		\bar{X}_{B_1}	\bar{X}_{B_2}	\bar{X}_{B_3}	

- a) **No significant main effects or interaction are present** If in a **between-subjects factorial analysis of variance** neither of the main effects or interaction is significant, in most instances it will not be productive for a researcher to conduct additional analysis of the data. If, however, prior to the data collection phase of a study a researcher happens to have planned any of the specific types of analyses to be discussed later in this section, he can still conduct them regardless of whether or not any of the F values are significant (and not be obliged to control the value of α_{FW}). Although one can also justify conducting additional analytical procedures that are unplanned, in such a case most statisticians believe that a researcher should control the familywise Type I error rate (α_{FW}), in order that it not exceed what would be considered to be a reasonable level.
- b) **One or both main effects are significant, but the interaction is not significant** When at least one of the F values is significant, the first question the researcher must ask prior to conducting any additional analytical procedures is whether or not the interaction is significant. When the interaction is not significant, a factorial design can essentially be conceptualized as being comprised of two separate single factor experiments. As such, both **simple** and **complex comparisons** can be conducted contrasting different means or sets of means that represent the

levels of each of the factors. Such comparisons involve contrasting within a specific factor the **marginal means** (i.e., the means of the p rows and the means of the q columns). In the case of Example 27.1, a simple comparison can be conducted in which two of the three levels of Factor B are compared with one another (i.e., \bar{X}_{B_1} versus \bar{X}_{B_2}), or a complex comparison in which a composite mean involving two levels of Factor B is compared with the mean of the third level of Factor B (i.e., $(\bar{X}_{B_2} + \bar{X}_{B_3})/2$ versus \bar{X}_{B_1}). If Factor B has four levels, a complex comparison contrasting two sets of composite means (each set representing a composite mean of two of the four levels) can be conducted (i.e., $(\bar{X}_{B_1} + \bar{X}_{B_2})/2$ versus $(\bar{X}_{B_3} + \bar{X}_{B_4})/2$). Since there are only two levels of Factor A, no additional comparisons are possible involving the means of the levels of that factor (i.e., the omnibus F value for Factor A represents the comparison \bar{X}_{A_1} versus \bar{X}_{A_2}). As is the case for the **single-factor between-subjects analysis of variance**, in designs in which one or both of the factors are comprised of more than three levels, it is possible to conduct an omnibus F test comparing the means of three or more of the levels of a specific factor. In addition to all of the aforementioned comparisons, within a given level of a specific factor, simple and complex comparisons can be conducted that contrast the means of specific groups that are a combination of both factors (i.e., a simple comparison such as $\bar{X}_{AB_{11}}$ versus $\bar{X}_{AB_{12}}$, or a complex comparison such as $\bar{X}_{AB_{11}}$ versus $(\bar{X}_{AB_{12}} + \bar{X}_{AB_{13}})/2$).⁸ It is worth reiterating that, whenever possible, comparisons should be planned prior to the data collection phase of a study, and that any comparisons which are conducted should address important theoretical and/or practical questions that underlie the hypotheses under study. In addition, the total number of comparisons that are conducted should be limited in number, and should not be redundant with respect to the information they provide.

c) **A significant interaction is present with or without one or more of the main effects being significant** As noted previously, when the interaction is significant the main effects are essentially rendered meaningless, since any main effects will have to be qualified in reference to the levels of a second factor. Thus, any comparison that involves the levels of a specific factor (e.g., \bar{X}_{B_1} versus \bar{X}_{B_2}) will reflect both the contribution of that factor, as well as the interaction between that factor and the second factor. For this reason, the most logical strategy to employ if a significant interaction is obtained is to test for what are referred to as **simple effects**. A test of a simple effect is essentially an analysis of variance evaluating all of the levels of one factor across only one level of the other factor. In the case of Example 27.1, two simple effects can be evaluated for Factor B. Specifically, an F test can be conducted which evaluates the scores of subjects on Factor B, but only for those subjects who serve under Level 1 of Factor A (i.e., an F ratio is computed for Groups AB_{11} , AB_{12} , and AB_{13}). A second simple effect for Factor B can be evaluated by contrasting the scores of subjects on Factor B, but only for those subjects who serve under Level 2 of Factor A (i.e., Groups AB_{21} , AB_{22} , and AB_{23}). In the case of Factor A, there are three possible simple effects that can be evaluated. Specifically, separate F tests can be conducted which evaluate the scores of subjects on Factor A for only those subjects who serve under: a) Level 1 of Factor B (i.e., Groups AB_{11} and AB_{21}); b) Level 2 of Factor B (i.e., Groups AB_{12} and AB_{22}); and c) Level 3 of Factor B (i.e., Groups AB_{13} and AB_{23}). In the event that one or more of the simple effects are significant, additional simple and complex comparisons contrasting specific groups within a given level of a factor can be conducted (e.g., a simple comparison such as $\bar{X}_{AB_{11}}$ versus $\bar{X}_{AB_{12}}$ or a complex comparison such as $\bar{X}_{AB_{11}}$ versus $(\bar{X}_{AB_{12}} + \bar{X}_{AB_{13}})/2$).

Description of analytical procedures (Including the following comparison procedures that are described for the **single-factor between-subjects analysis of variance**, which in this section, are described in reference to the **between-subjects factorial analysis of variance**: **Test 27a:**

Multiple t tests/Fisher's LSD test (which is equivalent to **linear contrasts**); **Test 27b: The Bonferroni–Dunn test**; **Test 27c: Tukey's HSD test**; **Test 27d: The Newman–Keuls test**; **Test 27e: The Scheffé test**; **Test 27f: The Dunnett test**)

Comparisons between the marginal means The equations that are employed in conducting simple and complex comparisons involving the marginal means are basically the same equations that are employed for conducting comparisons for the **single-factor between-subjects analysis of variance**. Thus, in comparing two marginal means or two sets of marginal means (in the case of complex comparisons), **linear contrasts** can be conducted when no attempt is made to control the value of α_{FW} (which will generally be the case for planned comparisons).⁹ In the case of either planned or unplanned comparisons where the value of α_{FW} is controlled, any of the multiple comparison procedures discussed under the **single-factor between-subjects analysis of variance** can be employed (i.e., **The Bonferroni–Dunn test**, **Tukey's HSD test**, **The Newman–Keuls test**, **The Scheffé test**, and **The Dunnett test**). The only difference in employing any of the latter comparison procedures with a factorial design is that the sample size employed in a comparison equation will reflect the number of subjects in each of the levels of the relevant factor. Thus, any comparison involving the marginal means of Factor A will involve nq subjects per group (in Example 27.1, $nq = (3)(3) = 9$), and any comparison involving the marginal means of Factor B will involve np subjects per group (in Example 27.1, $np = (3)(2) = 6$).

As an example, assume we want to compare the scores of subjects on two of the levels of Factor B — specifically Level 1 versus Level 3 (i.e., \bar{X}_{B_1} versus \bar{X}_{B_3}). If no attempt is made to control the value of α_{FW} , Equations 27.28–27.30 (which are the analogs of Equations 21.17–21.19 employed for conducting **linear contrasts** for the **single-factor between-subjects analysis of variance**) are employed to conduct a **linear contrast** comparing the two levels of Factor B (which within the framework of the comparison are conceptualized as two groups). Note that in Equation 27.28 the value np represents the number of subjects who served under each level of Factor B, and $[\sum(c_{B_k})(\bar{X}_{B_k})]^2$ will equal the squared difference between the means of the two levels of Factor B that are being compared (i.e., in the case of the comparison under discussion, $[\sum(c_{B_k})(\bar{X}_{B_k})]^2 = (\bar{X}_{B_1} - \bar{X}_{B_3})^2$).

$$SS_{B \text{ comp}} = \frac{np[\sum(c_{B_k})(\bar{X}_{B_k})]^2}{\sum c_{B_k}^2} \quad (\text{Equation 27.28})$$

$$MS_{B \text{ comp}} = \frac{SS_{B \text{ comp}}}{df_{B \text{ comp}}} \quad (\text{Equation 27.29})$$

$$F_{B \text{ comp}} = \frac{MS_{B \text{ comp}}}{MS_{WG}} \quad (\text{Equation 27.30})$$

The data from Example 27.1 are now employed in Equations 27.28–27.30 to conduct the comparison \bar{X}_{B_1} versus \bar{X}_{B_3} . Note that since Levels 1 and 3 of Factor B constitute the groups that are involved in the comparison, the coefficients for the comparison are $c_{B_1} = +1$, $c_{B_2} = 0$, $c_{B_3} = -1$. Thus, $\sum c_{B_k}^2 = 2$ and $[\sum(c_{B_k})(\bar{X}_{B_k})]^2 = (\bar{X}_{B_1} - \bar{X}_{B_3})^2 = (6.5 - 2.5)^2 = (4)^2 = 16$. Substituting the appropriate values in Equation 27.28, the value $SS_{B \text{ comp}} = 48$ is computed.

$$SS_{B \text{ comp}} = \frac{(3)(2)(4)^2}{2} = 48$$

Since all **linear contrasts** represent a **single degree of freedom comparison**, $df_{B \text{ comp}} = 1$. Employing Equations 27.29 and 27.30, the values $MS_{B \text{ comp}} = 48$ and $F_{B \text{ comp}} = 48$ are computed. Note that the value $MS_{WG} = 1$ computed for the omnibus F test is employed in the denominator of Equation 27.30.

$$MS_{B \text{ comp}} = \frac{48}{1} = 48$$

$$F_{B \text{ comp}} = \frac{48}{1} = 48$$

The value $F_{B \text{ comp}} = 48$ is evaluated with **Table A10**. Employing the latter table, the appropriate degrees of freedom for the numerator and denominator are $df_{\text{num}} = df_{B \text{ comp}} = 1$ and $df_{\text{den}} = df_{WG} = 12$. For $df_{\text{num}} = 1$ and $df_{\text{den}} = 12$, the tabled critical .05 and .01 values are $F_{.05} = 4.75$ and $F_{.01} = 9.33$. Since the obtained value $F_{\text{comp}} = 48$ is greater than the aforementioned critical values, the nondirectional alternative hypothesis $H_1: \mu_{B_1} \neq \mu_{B_3}$ is supported at both the .05 and .01 levels.

Equations 27.31–27.33 are employed to evaluate comparisons involving the levels of Factor A.

$$SS_{A \text{ comp}} = \frac{nq[\sum(c_{A_j})(\bar{X}_{A_j})]^2}{\sum c_{A_j}^2} \quad (\text{Equation 27.31})$$

$$MS_{A \text{ comp}} = \frac{SS_{A \text{ comp}}}{df_{A \text{ comp}}} \quad (\text{Equation 27.32})$$

$$F_{A \text{ comp}} = \frac{MS_{A \text{ comp}}}{MS_{WG}} \quad (\text{Equation 27.33})$$

Note that in Equation 27.31 nq represents the sample size, which in this case is the number of subjects who serve in each level of Factor A. The value $[\sum(c_{A_j})(\bar{X}_{A_j})]^2$ is equal to $(\bar{X}_{A_x} - \bar{X}_{A_y})^2$, which is the squared difference between the two means involved in the comparison (where x and y represent the levels of Factor A that are employed in the comparison).

As is the case with comparisons conducted for a **single-factor between-subjects analysis of variance**, a CD value can be computed for any comparison. Recollect that a CD value represents the minimum required difference in order for two means to differ significantly from one another. To demonstrate this, two CD values will be computed for the comparison \bar{X}_{B_1} versus \bar{X}_{B_3} . Specifically, CD_{LSD} and CD_S will be computed. CD_{LSD} (which is the CD value associated with the **linear contrast** that is conducted with Equations 27.28–27.30) is the lowest possible difference that can be computed with any of the available comparison procedures. CD_S (the value for the **Scheffé test**), on the other hand, computes the largest CD value from the methods that are available. If the obtained difference for a comparison is less than CD_{LSD} , the null hypothesis will be retained, whereas if it is larger than CD_S it will be rejected. For the purpose

of this discussion, it will be assumed that an obtained difference that is larger than CD_{LSD} but less than CD_S will be relegated to the **suspend judgement** category.¹⁰

Equation 27.34 is employed to compute the value $CD_{LSD} = 1.25$ for the **simple comparison** \bar{X}_{B_1} versus \bar{X}_{B_3} , for $\alpha = .05$. In point of fact, the CD_{LSD} value computed with Equation 27.34 applies to all three simple comparisons that can be conducted with respect to Factor B (i.e., $\bar{X}_{B_1} - \bar{X}_{B_2} = 6.5 - 5.5 = 1$; $\bar{X}_{B_1} - \bar{X}_{B_3} = 6.5 - 2.5 = 4$; $\bar{X}_{B_2} - \bar{X}_{B_3} = 5.5 - 2.5 = 3$).

$$CD_{LSD} = \sqrt{F_{(1, WG)}} \sqrt{\frac{2MS_{WG}}{np}} = \sqrt{4.75} \sqrt{\frac{(2)(1)}{(3)(2)}} = 1.25 \quad \text{(Equation 27.34)}$$

In order to differ significantly at the .05 level, the means of any two levels of Factor B must differ from one another by at least 1.25 units. Thus, the differences $\bar{X}_{B_1} - \bar{X}_{B_3} = 4$ and $\bar{X}_{B_2} - \bar{X}_{B_3} = 3$ are significant, while the difference $\bar{X}_{B_1} - \bar{X}_{B_2} = 1$ is not.

Note that Equation 27.34 is identical to Equation 21.24 employed for computing the CD_{LSD} value for the **single-factor between-subjects analysis of variance**, except for the fact that in Equation 27.34, np subjects are employed per group/level of Factor B. In Equation 27.34, the value $F_{(1, WG)} = 4.75$ is the tabled critical .05 F value for df_{num} and df_{den} , which represent the degrees of freedom associated with the $F_{B \text{ comp}}$ value computed with Equation 27.30.

Equations 27.35 and 27.36, which are analogous to Equation 21.25 (which is the generic equation for both simple and complex comparisons for CD_{LSD} for the **single-factor between-subjects analysis of variance**), are, respectively, the generic equations for Factors A and B for computing CD_{LSD} .

$$CD_{LSD} = \sqrt{F_{(1, WG)}} \sqrt{\frac{(\sum c_{A_j}^2)(MS_{WG})}{nq}} \quad \text{(Equation 27.35)}$$

$$CD_{LSD} = \sqrt{F_{(1, WG)}} \sqrt{\frac{(\sum c_{B_k}^2)(MS_{WG})}{np}} \quad \text{(Equation 27.36)}$$

At this point the **Scheffé test** will be employed to conduct the simple comparison \bar{X}_{B_1} versus \bar{X}_{B_3} . Equation 27.37, which is analogous to Equation 21.32 (which is the equation for simple comparisons for CD_S for the **single-factor between-subjects analysis of variance**), is employed to compute the value $CD_S = 1.61$, with $\alpha_{FW} = .05$. The value $F_{(B, WG)} = 3.89$ used in Equation 27.37 is the tabled critical .05 F value employed in evaluating the main effect for Factor B in the omnibus F test.

(Equation 27.37)

$$CD_S = \sqrt{(q - 1)F_{df_{(B, WG)}}} \sqrt{\frac{2MS_{WG}}{np}} = \sqrt{(3 - 1)(3.89)} \sqrt{\frac{(2)(1)}{(3)(2)}} = 1.61$$

Thus, in order to differ significantly at the .05 level, the means of any two levels of Factor B must differ from one another by at least 1.61 units. As is the case when $CD_{LSD} = 1.25$ is computed, the differences $\bar{X}_{B_1} - \bar{X}_{B_3} = 4$ and $\bar{X}_{B_2} - \bar{X}_{B_3} = 3$ are significant, while the difference $\bar{X}_{B_1} - \bar{X}_{B_2} = 1$ is not.

Equations 27.38 and 27.39, which are analogous to Equation 21.33 (which is the generic equation for both simple and complex comparisons for CD_S for the **single-factor between-subjects analysis of variance**), are, respectively, the generic equations for Factors A and B for computing CD_S . Note that in conducting comparisons involving the levels of Factor A, the value $F_{(A, WG)}$ employed in Equation 27.38 is the tabled critical F value at the prespecified level of significance used in evaluating the main effect for Factor A in the omnibus F test.

$$CD_S = \sqrt{(p - 1)F_{df_{(A, WG)}}} \sqrt{\frac{(\sum c_{A_j}^2)(MS_{WG})}{nq}} \quad (\text{Equation 27.38})$$

$$CD_S = \sqrt{(q - 1)F_{df_{(B, WG)}}} \sqrt{\frac{(\sum c_{B_k}^2)(MS_{WG})}{np}} \quad (\text{Equation 27.39})$$

In closing the discussion of the **Scheffé test**, it should be noted that since Equation 27.37 only takes into account those comparisons that are possible involving the levels of Factor B, it may not be viewed as imposing adequate control over α_{FW} if one intends to conduct additional comparisons involving the levels of Factor A and/or specific groups that are a combination of both factors. Because of this, some sources make a distinction between the **familywise error rate** (α_{FW}) and the **experimentwise error rate**. Although in the case of a single factor experiment the two values will be identical, in a multifactor experiment, a **familywise error rate** can be computed for comparisons within each factor as well as for comparisons between groups that are based on combinations of the factors. The **experimentwise error rate** will be a composite error rate which will be the result of combining all of the **familywise error rates**. Thus, in the above example if one intends to conduct additional comparisons involving the levels of Factor A and/or groups that are combinations of both factors, one can argue that the **Scheffé test** as employed does not impose sufficient control over the value of the **experimentwise error rate**. Probably the simplest way to deal with such a situation is to conduct a more conservative test in evaluating any null hypotheses involving the levels of Factor A, Factor B, or groups that are combinations of both factors (i.e., evaluate a null hypothesis at the .01 level instead of at the .05 level).

Evaluation of an omnibus hypothesis involving more than two marginal means If the interaction is not significant, it is conceivable that a researcher may wish to conduct an F test on three or more marginal means in a design where the factor involved has four or more levels. In other words, if in Example 27.1 there were four levels on Factor B instead of three, one might want to evaluate the null hypothesis $H_0: \mu_{B_1} = \mu_{B_2} = \mu_{B_3}$. The logic that is employed in conducting such an analysis for the **single-factor between-subjects analysis of variance** can be extended to a factorial design. Specifically, in the case of a 2×4 design, a **between-subjects factorial analysis of variance** employing all of the data is conducted initially. Upon determining that the interaction is not significant, a **single-factor between-subjects analysis of variance** can then be conducted employing only the data for the three levels of Factor B in which the researcher is interested (i.e., B_1 , B_2 , and B_3). The following F ratio is computed: $F_{(B_1/B_2/B_3)} = MS_{BG_{(B_1/B_2/B_3)}} / MS_{WG}$. Note that the mean square value in the numerator is based on the between-groups variability in the **single-factor between-subjects analysis of variance** that involves only the data for levels B_1 , B_2 , and B_3 of Factor B. The degrees of freedom associated with the numerator of the F ratio is 2, since it is based on the number of levels of Factor B evaluated with the **single-factor between-subjects analysis of variance** (i.e.,

$df_{(B_1/B_2/B_3)} = 3 - 1 = 2$). The mean square and degrees of freedom for the denominator of the F ratio are the within-groups mean square and degrees of freedom computed for the **between-subjects factorial analysis of variance** when the full set of data is employed (i.e., the data for all four levels of Factor B). For further clarification of the aforementioned procedure the reader should review Section VI of the **single-factor between-subjects analysis of variance**.

Comparisons between specific groups that are a combination of both factors The procedures employed for comparing the marginal means can also be employed to evaluate differences between specific groups that are a combination of both factors (e.g., a comparison such as $\bar{X}_{AB_{11}}$ versus $\bar{X}_{AB_{12}}$). Such differences are most likely to be of interest when an interaction is present. It should be noted that these are not the only types of comparisons that can provide more specific information regarding the nature of an interaction. A more comprehensive discussion of further analysis of an interaction can be found in books that specialize in the analysis of variance. Keppel (1991), among others, provides an excellent discussion of this general subject.

In comparing specific groups with one another, the same equations are essentially employed that are used for the comparison of marginal means, except for the fact that the equations must be modified in order to accommodate the sample size of the groups. Both simple and complex comparisons can be conducted. As an example, let us assume we want to conduct a **linear contrast** for the simple comparison $\bar{X}_{AB_{11}}$ versus $\bar{X}_{AB_{12}}$. Equation 27.40 is employed for conducting such a comparison. Note that the latter equation has the same basic structure as Equations 27.28 and 27.31, but is based on the sample size of n , which is the sample size of each of the $p \times q$ groups.

$$SS_{\text{comp}} = \frac{n[\sum(c_{AB_{jk}})(\bar{X}_{AB_{jk}})]^2}{\sum c_{AB_{jk}}^2} \quad (\text{Equation 27.40})$$

In Equation 27.40 the value $[\sum(c_{AB_{jk}})(\bar{X}_{AB_{jk}})]^2$ is equal to the squared difference between the means of the two groups that are being compared (i.e., for the comparison under discussion it yields the same value as $(\bar{X}_{AB_{11}} - \bar{X}_{AB_{12}})^2$). Note that since only two of the $p \times q = 6$ groups are involved in the comparison, the coefficients for the comparison are $c_{AB_{11}} = +1$, $c_{AB_{12}} = -1$, and $c_{AB_{jk}} = 0$ for the remaining four groups. Thus, $[\sum(c_{AB_{jk}})(\bar{X}_{AB_{jk}})]^2 = (\bar{X}_{AB_{11}} - \bar{X}_{AB_{12}})^2 = (10 - 7)^2 = (3)^2 = 9$ and $\sum c_{AB_{jk}}^2 = 2$. Substituting the appropriate values in Equation 27.40, the value $SS_{\text{comp}} = 13.5$ is computed.

$$SS_{\text{comp}} = \frac{(3)(3)^2}{2} = 13.5$$

Employing Equations 21.18 and 21.19, the values $MS_{\text{comp}} = 13.5$ and $F_{\text{comp}} = 13.5$ are computed.

$$MS_{\text{comp}} = \frac{SS_{\text{comp}}}{df_{\text{comp}}} = \frac{13.5}{1} = 13.5$$

$$F_{\text{comp}} = \frac{MS_{\text{comp}}}{MS_{\text{WG}}} = \frac{13.5}{1} = 13.5$$

Employing **Table A10**, the appropriate degrees of freedom for the numerator and denominator are $df_{\text{num}} = df_{\text{comp}} = 1$ (since the comparison is a **single degree of freedom comparison**) and $df_{\text{den}} = df_{\text{WG}} = 12$. For $df_{\text{num}} = 1$ and $df_{\text{den}} = 12$, the tabled critical .05 and .01 values are $F_{.05} = 4.75$ and $F_{.01} = 9.33$. Since the obtained value $F_{\text{comp}} = 13.5$ is greater than the aforementioned critical values, the nondirectional alternative hypothesis $H_1: \mu_{AB_{11}} \neq \mu_{AB_{12}}$ is supported at both the .05 and .01 levels.

CD_{LSD} and CD_S values will now be computed for the above comparison, for $\alpha = .05$. CD_{LSD} is computed with Equation 27.41 (which is identical to Equation 21.24 employed to compute CD_{LSD} for the **single-factor between-subjects analysis of variance**). Note that the sample size employed in Equation 27.41 is $n = n_{AB_{jk}} = 3$. Substituting the appropriate values in Equation 27.41, the value $CD_{\text{LSD}} = 1.78$ is computed.

$$CD_{\text{LSD}} = \sqrt{F_{(1, \text{WG})}} \sqrt{\frac{2MS_{\text{WG}}}{n}} = \sqrt{4.75} \sqrt{\frac{(2)(1)}{3}} = 1.78 \quad (\text{Equation 27.41})$$

Since in order to differ significantly at the .05 level the means of any two groups must differ from one another by at least 1.78 units, the difference $\bar{X}_{AB_{11}} - \bar{X}_{AB_{12}} = 3$ is significant. If we conduct comparisons for all 15 possible differences between pairs of groups (i.e., all simple comparisons), any difference that is equal to or greater than 1.78 units is significant at the .05 level.¹¹ Recollect, though, that since the computation of a CD_{LSD} value does not control the value of α_{FW} , the **per comparison Type I error rate** will equal .05.

Equation 27.42 (which is analogous to Equation 21.25 employed for the **single-factor between-subjects analysis of variance**) is the generic form of Equation 27.41 that can be employed for both simple and complex comparisons.

$$CD_{\text{LSD}} = \sqrt{F_{(1, \text{WG})}} \sqrt{\frac{(\sum c_{AB_{jk}}^2)(MS_{\text{WG}})}{n}} \quad (\text{Equation 27.42})$$

CD_S is computed with Equation 27.43 (which is analogous to Equation 21.32 employed to compute CD_S for the **single-factor between-subjects analysis of variance**). Substituting the appropriate values in Equation 27.43, the value $CD_S = 3.22$ is computed. The value $F_{df_{(BG, \text{WG})}} = 3.11$ used in Equation 27.43 is the tabled critical .05 F value for $df_{\text{num}} = df_{\text{BG}} = pq - 1 = (2)(3) - 1 = 5$ and $df_{\text{den}} = df_{\text{WG}} = 12$ employed in the omnibus F test.

$$\begin{aligned} CD_S &= \sqrt{(pq - 1)F_{df_{(BG, \text{WG})}}} \sqrt{\frac{2MS_{\text{WG}}}{n}} \\ &= \sqrt{[(2)(3) - 1](3.11)} \sqrt{\frac{(2)(1)}{3}} = 3.22 \end{aligned} \quad (\text{Equation 27.43})$$

Thus, in order for any pair of means to differ significantly, the difference between the two means must be equal to or greater than 3.22 units. Since the difference $\bar{X}_{AB_{11}} - \bar{X}_{AB_{12}} = 3$ is less than $CD_S = 3.22$, the null hypothesis cannot be rejected if the **Scheffé test** is employed. Thus, the nondirectional alternative hypothesis $H_1: \mu_{AB_{11}} \neq \mu_{AB_{12}}$ is not supported.

Equation 27.44 (which is analogous to Equation 21.33 employed for the **single-factor**

between-subjects analysis of variance) is the generic form of Equation 27.43 that can be employed for both simple and complex comparisons.

$$CD_S = \sqrt{(pq - 1)F_{df_{(BG, WG)}}} \sqrt{\frac{(\sum c_{AB_{jk}}^2)(MS_{WG})}{n}} \quad (\text{Equation 27.44})$$

Since the **linear contrast** procedure yields a significant difference and the **Scheffé test** does not, one might want to **suspend judgement** with respect to the comparison $\bar{X}_{AB_{11}}$ versus $\bar{X}_{AB_{12}}$ until a replication study is conducted. However, it is certainly conceivable that many researchers might consider the **Scheffé test** to be too conservative a procedure. Thus, one might elect to use a less conservative procedure such as **Tukey's HSD test**. Equation 27.45 (which is analogous to Equation 21.31 employed to compute CD_{HSD} for the **single-factor between-subjects analysis of variance**) is employed to compute CD_{HSD} . The value $q_{(pq, df_{WG})} = 4.75$ in Equation 27.45 is the value of the **Studentized range statistic** in [Table A13 \(Table of the Studentized Range Statistic\)](#) in the [Appendix](#) for $k = pq = 6$ and $df_{WG} = 12$.

$$CD_{HSD} = q_{(pq, df_{WG})} \sqrt{\frac{MS_{WG}}{n}} = 4.75 \sqrt{\frac{1}{3}} = 2.74 \quad (\text{Equation 27.45})$$

Since $CD_{HSD} = 2.74$ is less than $\bar{X}_{AB_{11}} - \bar{X}_{AB_{12}} = 3$, we can conclude that the difference between the groups is significant.¹²

The computation of a confidence interval for a comparison The same procedure described for computing a confidence interval for a comparison for the **single-factor between-subjects analysis of variance** can also be employed for the **between-subjects factorial analysis of variance**. Specifically, the following procedure is employed for computing a confidence interval for any of the methods described in this section: The obtained CD value is added to and subtracted from the obtained difference between the two means (or sets of means in the case of a complex comparison). The resulting range of values defines the confidence interval. The 95% confidence interval will be associated with a computed $CD_{.05}$ value, and the 99% confidence interval will be associated with a computed $CD_{.01}$ value. To illustrate the computation of a confidence interval, the 95% confidence interval for the value $CD_{HSD} = 2.74$ computed for the comparison $\bar{X}_{AB_{11}}$ versus $\bar{X}_{AB_{12}}$ is demonstrated below.

$$CI_{.95} = (\bar{X}_{AB_{11}} - \bar{X}_{AB_{12}}) \pm CD_{HSD} = 3 \pm 2.74$$

Thus, the researcher can be 95% sure (or the probability is .95) that the mean of the population represented by Group AB_{11} is between .26 and 5.74 units larger than the mean of the population represented by Group AB_{12} . This result can be stated symbolically as follows: $.26 \leq (\mu_{AB_{11}} - \mu_{AB_{12}}) \leq 5.74$.

Analysis of simple effects Earlier in this section it was noted that the most logical strategy to employ when a significant interaction is detected is to initially test for what is referred to as **simple effects**. A test of a **simple effect** is essentially an analysis of variance evaluating all of the levels of one factor across only one level of the other factor. The analysis of simple effects will be illustrated with Example 27.1 by evaluating the simple effects of Factor B. Specifically, an

F test will be conducted to evaluate the scores of subjects on the three levels of Factor B, but only the nq subjects who served under Level 1 of Factor A (i.e., an F ratio will be computed evaluating the Groups AB_{11} , AB_{12} , and AB_{13}). This represents the analysis of the simple effect of Factor B at level A_1 . An analysis of a second simple effect (which represents the analysis of the simple effect of Factor B at level A_2) will evaluate the scores of subjects on the three levels of Factor B, but only the nq subjects who served under Level 2 of Factor A (i.e., Groups AB_{21} , AB_{22} , and AB_{23}).

Although it will not be done in reference to Example 27.1, since an interaction is present a comprehensive analysis of the data would also involve evaluating the simple effects of Factor A. There are three simple effects of Factor A that can be evaluated, each one involving comparing the scores of subjects on Factor A, but employing only the np subjects who served under one of the three levels of Factor B. The three simple effects of Factor A involve the following contrasts: 1) The simple effect of Factor A at Level B_1 : $\bar{X}_{AB_{11}}$ versus $\bar{X}_{AB_{21}}$; 2) The simple effect of Factor A at Level B_2 : $\bar{X}_{AB_{12}}$ versus $\bar{X}_{AB_{22}}$; and 3) The simple effect of Factor A at Level B_3 : $\bar{X}_{AB_{13}}$ versus $\bar{X}_{AB_{23}}$.¹³

In order to evaluate a simple effect, it is necessary to initially compute a sum of squares for the specific effect. Thus, in evaluating the simple effects of Factor B it is necessary to compute a sum of squares for Factor B at Level 1 of Factor A ($SS_{B \text{ at } A_1}$) and a sum of squares for Factor B at Level 2 of Factor A ($SS_{B \text{ at } A_2}$). Upon computing all of the sums of squares for the simple effects for a specific factor, F ratios are computed for each of the simple effects by dividing the mean square for a simple effect (which is obtained by dividing the simple effect sum of squares by its degrees of freedom) by the within-groups mean square derived for the factorial analysis of variance. This procedure will now be demonstrated for the simple effects of Factor B.

Equation 27.46 is employed to compute the sum of squares for each of the simple effects. If $\sum X_{AB_j}$ represents the sum of the scores on Level j of Factor A of subjects who serve under a specific level of Factor B, the notation $\sum[(\sum X_{AB_j})^2/n]$ in Equation 27.46 indicates that the sum of the scores for each level of Factor B at a given level of Factor A is squared, divided by n , and the q squared sums are summed. The notation $(\sum \sum X_{AB_j})^2$ represents the square of the sum of scores of the nq subjects who serve under the specified level of Factor A.¹⁴

$$SS_{B \text{ at } A_j} = \sum \left[\frac{(\sum X_{AB_j})^2}{n} \right] - \frac{(\sum \sum X_{AB_j})^2}{nq} \quad (\text{Equation 27.46})$$

$$SS_{B \text{ at } A_1} = \sum \left[\frac{(\sum X_{AB_1})^2}{n} \right] - \frac{(\sum \sum X_{AB_1})^2}{nq} = \left[\frac{(30)^2 + (21)^2 + (12)^2}{3} \right] - \frac{(63)^2}{(3)(3)} = 54$$

$$SS_{B \text{ at } A_2} = \sum \left[\frac{(\sum X_{AB_2})^2}{n} \right] - \frac{(\sum \sum X_{AB_2})^2}{nq} = \left[\frac{(9)^2 + (12)^2 + (3)^2}{3} \right] - \frac{(24)^2}{(3)(3)} = 14$$

Table 27.6 summarizes the analysis of variance for the simple effects of Factor B. Note that for each of the simple effects, the degrees of freedom for the effect is $df_{B \text{ at } A_j} = q - 1 = 3 - 1 = 2$ (which equals df_B employed for the **between-subjects factorial analysis of variance**). The mean square for each simple effect is obtained by dividing the sum of squares for the simple effect by its degrees of freedom. The F value for each simple effect is obtained by dividing the mean square for the simple effect by $MS_{WG} = 1$ computed for the factorial analysis of variance. Thus, $F_{B \text{ at } A_1} = 27/1 = 27$ and $F_{B \text{ at } A_2} = 7/1 = 7$.

Table 27.6 Analysis of Simple Effects of Factor B

Source of variation	<i>SS</i>	<i>df</i>	<i>MS</i>	<i>F</i>
B at A_1	54	2	27	27
B at A_2	14	2	7	7
Within-groups	12	12	1	

Employing **Table A10**, the degrees of freedom used in evaluating each of the simple effects are $df_{\text{num}} = df_{B \text{ at } A_j} = 2$ and $df_{\text{den}} = df_{WG} = 12$. Since both of the obtained values $F_{B \text{ at } A_1} = 27$ and $F_{B \text{ at } A_2} = 7$ are greater than $F_{.05} = 3.89$ and $F_{.01} = 6.93$ (which are the tabled critical values for $df_{\text{num}} = 2$ and $df_{\text{den}} = 12$), each of the simple effects is significant at both the .05 and .01 levels. On the basis of the result of the analysis of the simple effects of Factor B, we can conclude that within each level of Factor A there is at least one simple or complex comparison involving the levels of Factor B that is significant.

As noted earlier, when one or more of the simple effects is significant, additional simple and complex comparisons contrasting specific groups can be conducted. Thus, for Level 1 of Factor A, simple comparisons between $\bar{X}_{AB_{11}}$, $\bar{X}_{AB_{12}}$, and $\bar{X}_{AB_{13}}$, as well as complex comparisons (such as $\bar{X}_{AB_{11}}$ versus $(\bar{X}_{AB_{12}} + \bar{X}_{AB_{13}})/2$) can clarify the locus of the significant simple effect.

If the homogeneity of variance assumption of the **between-subjects factorial analysis of variance** (which is discussed in the next section) is violated, in computing the *F* ratios for the simple effects, a researcher can justify employing a MS_{WG} value that is just based on the groups involved in analyzing a specific simple effect, instead of the value of MS_{WG} computed for the factorial analysis of variance. If the latter is done, the within-groups degrees of freedom employed in the analysis of the simple effects of Factor B becomes $df_{WG} = q(n - 1)$ instead of $df_{WG} = pq(n - 1)$. Since the within-groups degrees of freedom is smaller if $df_{WG} = q(n - 1)$ is employed, the test will be less powerful than a test employing $df_{WG} = pq(n - 1)$. The loss of power can be offset, however, if the new value for MS_{WG} is lower than the value derived for the omnibus *F* test.¹⁵

The reader should take note of the fact that the variability within each of the simple effects is the result of contributions from both the main effect on the factor for which the simple effect is being evaluated (Factor B in our example), as well as any interaction between the two factors. For this reason, the total of the sum of squares for each of the simple effects for a given factor will be equal to the interaction sum of squares (SS_{AB}) plus the sum of squares for that factor (SS_B). This can be confirmed by the fact that in our example the following is true:

$$[(SS_{B \text{ at } A_1} = 54) + (SS_{B \text{ at } A_2} = 14)] = [(SS_{AB} = 16) + (SS_B = 52)] = 68$$

It should be noted that analysis of simple effects in and of itself cannot provide definitive evidence with regard to the presence or absence of an interaction. In point of fact, it is possible for only one of two simple effects to be significant, and yet the value of F_{AB} computed for the factorial analysis of variance may not be significant. For a full clarification of this issue the reader should consult Keppel (1991).

2. Evaluation of the homogeneity of variance assumption of the between-subjects factorial analysis of variance The homogeneity of variance assumption discussed in reference to the **single-factor between-subjects analysis of variance** is also an assumption of the **between-subjects factorial analysis of variance**. Since both tests employ the same protocol in evaluating this assumption, prior to reading this section the reader should review the relevant material for evaluating the homogeneity of variance assumption (through use of **Hartley's F_{max} test** (**Test**

11a)) in Section VI of the **single-factor between-subjects analysis of variance** (as well as the material on **Hartley's F_{\max} test** in Section VI of the **t test for two independent samples**).

In the case of the **between-subjects factorial analysis of variance**, evaluation of the homogeneity of variance assumption requires the researcher to compute the estimated population variances for each of the pq groups. The latter values are computed with Equation I.5. As it turns out, the value of the estimated population variance for all six groups equals $\tilde{s}_{AB_{jk}}^2 = 1$. This can be demonstrated below for Group AB_{11} .

$$\tilde{s}_{AB_{11}}^2 = \frac{\sum X_{AB_{11}}^2 - \frac{(\sum X_{AB_{11}})^2}{n_{AB_{11}}}}{n_{AB_{11}} - 1} = \frac{302 - \frac{(30)^2}{3}}{3 - 1} = 1$$

Upon determining that the value of both the largest and smallest of the estimated population variances equals 1, Equation 21.37 is employed to compute the value of the F_{\max} statistic. Employing Equation 21.37, the value $F_{\max} = 1$ is computed.

$$F_{\max} = \frac{\tilde{s}_L^2}{\tilde{s}_S^2} = \frac{1}{1} = 1$$

In order to reject the null hypothesis ($H_0: \sigma_L^2 = \sigma_S^2$) and thus conclude that the homogeneity of variance assumption is violated, the obtained F_{\max} value must be equal to or greater than the tabled critical value at the prespecified level of significance. Employing **Table A9 (Table of the F_{\max} Distribution)** in the **Appendix**, we determine that the tabled critical F_{\max} values for $n = n_{AB_{jk}} = 3$ and $k = pq = 6$ groups are $F_{\max_{.05}} = 266$ and $F_{\max_{.01}} = 1362$. Since the obtained value $F_{\max} = 1$ is less than $F_{\max_{.05}} = 266$, the null hypothesis cannot be rejected. In other words, the alternative hypothesis indicating the presence of heterogeneity of variance is not supported. The latter should be obvious without the use of the F_{\max} test, since the same value is computed for the variance of each of the groups.

In instances where the homogeneity of variance assumption is violated, the researcher should employ one of the strategies recommended for heterogeneity of variance that are discussed in Section VI of the **single-factor between-subjects analysis of variance**. The simplest strategy is to use a more conservative test (i.e., employ a lower α level) in evaluating the three sets of hypotheses for the factorial analysis of variance.¹⁶

3. Computation of the power of the between-subjects factorial analysis of variance Prior to reading this section the reader should review the procedure described for computing the power of the **single-factor between-subjects analysis of variance**, since the latter procedure can be generalized to the **between-subjects factorial analysis of variance**. In determining the appropriate sample size for a factorial design, a researcher must consider the predicted effect size for each of the factors, as well as the magnitude of any predicted interactions. Thus, in the case of Example 27.1, prior to the experiment, a separate power analysis can be conducted with respect to the main effect for Factor A, the main effect for Factor B, and the interaction between the two factors. The sample size the researcher should employ will be the largest of the sample sizes derived from analyzing the predicted effects associated with the two factors and the interaction. As is the case for the **single-factor between-subjects analysis of variance**, such an analysis will require the researcher to estimate the means of all of the experimental groups, as well as the value of error/within-groups variability (i.e., σ_{WG}^2).

Equation 27.47, which contains the same basic elements that comprise Equation 21.38, is the general equation that is employed for determining the minimum sample size necessary in order to achieve a specified power with regard to either of the main effects or the interaction.

$$\phi = \sqrt{(\text{number of observations}) \left[\frac{\sum d^2}{(df_{\text{effect}} + 1)(\sigma_{WG}^2)} \right]} \quad (\text{Equation 27.47})$$

The following should be noted with respect to Equation 27.47:

a) The value employed for the number of observations will equal nq for Factor A, np for Factor B, and n for the interaction.

b) $\sum d^2$ represents the sum of the squared deviation scores. This value is obtained as follows: 1) For **Factor A**, p deviation scores are computed by subtracting the estimated grand mean (μ_G) from each of the estimated means of the levels of Factor A (i.e., $d_{A_j} = \mu_{A_j} - \mu_G$). $\sum d^2$, the sum of the squared deviation scores, is obtained by squaring the p deviation scores and summing the resulting values; 2) For **Factor B**, q deviation scores are computed by subtracting the estimated grand mean from each of the estimated means of the levels of Factor B (i.e., $d_{B_k} = \mu_{B_k} - \mu_G$). The sum of the squared deviation scores is obtained by squaring the q deviation scores and summing the resulting values; and 3) For the interaction, pq deviation scores are computed — one for each of the groups. A deviation score is computed for each group by employing the following equation: $d_{AB_{jk}} = \mu_{AB_{jk}} - \mu_{A_j} - \mu_{B_k} + \mu_G$. The latter equation indicates the following: The mean of the group is estimated ($\mu_{AB_{jk}}$), after which both the estimated mean of the level of Factor A the group serves under (μ_{A_j}) and the estimated mean of the level of Factor B the group serves under (μ_{B_k}) are subtracted from the estimated mean of the group. The estimated grand mean (μ_G) is then added to this result. The resulting value represents the deviation score for that group. Upon computing a deviation score for each of the pq groups, the pq deviation scores are squared, after which the resulting squared deviation scores are summed. The resulting value equals $\sum d^2$.

c) $(df_{\text{effect}} + 1)$ for Factor A equals $df_A + 1 = p$. $(df_{\text{effect}} + 1)$ for Factor B equals $df_B + 1 = q$. $(df_{\text{effect}} + 1)$ for the interaction equals $df_{AB} + 1 = (p - 1)(q - 1) + 1$.

d) σ_{WG}^2 is the estimate of the population variance for any one of the pq groups (which are assumed to have equal variances if the homogeneity of variance assumption is true). If a power analysis is conducted after the data collection phase of a study, it is logical to employ MS_{WG} as the estimate of σ_{WG}^2 .¹⁷

To illustrate the use of Equation 27.47, the power of detecting the main effect on Factor B will be computed. Let us assume that based on previous research, prior to evaluating the data we estimate the following values: $\mu_{B_1} = 7$, $\mu_{B_2} = 5$, $\mu_{B_3} = 3$. Since we know that $\mu_G = (\mu_{B_1} + \mu_{B_2} + \mu_{B_3})/q$, $\mu_G = (7 + 5 + 3)/3 = 5$.¹⁸ It will also be assumed that the estimated value for error variability is $\sigma_{WG}^2 = 1.5$. The relevant values are now substituted in Equation 27.47.

$$\phi = \sqrt{np \left[\frac{\sum (\mu_{B_k} - \mu_G)^2}{(q)(\sigma_{WG}^2)} \right]} = \sqrt{n(2) \left[\frac{(7-5)^2 + (5-5)^2 + (3-5)^2}{(3)(1.5)} \right]} = 1.89\sqrt{n}$$

If we employ $n = 3$ subjects per groups (as is the case in Example 27.1), the value $\phi = 3.27$ is computed: $\phi = 1.89\sqrt{3} = 3.27$. Employing **Table A15 (Graphs of the Power Function for the Analysis of Variance)** in the **Appendix**, we use the set of power curves for

$df_{\text{num}} = df_{\text{effect}} = df_B = 2$, and within that set employ the curve for $df_{\text{den}} = df_{WG} = 12$, for $\alpha = .05$. Since a perpendicular line erected from the value $\phi = 3.27$ on the abscissa to the curve for $df_{WG} = 12$ is beyond the highest point on the curve, the power of the test for the estimated effect on Factor B will be 1 if $n = 3$ subjects are employed per group. Thus, there is a 100% likelihood that an effect equal to or larger than the one stipulated by the values employed in Equation 27.47 will be detected.

Although it will not be demonstrated here, to conduct a thorough power analysis it is necessary to also determine the minimum required sample sizes required to achieve what a researcher would consider to be the minimum acceptable power for identifying the estimated effects for Factor A and the interaction. The largest of the values computed for n for each of the three power analyses is the sample size that should be employed for each of the pq groups in the study. For a more comprehensive discussion on computing the power of the **between-subjects factorial analysis of variance** the reader should consult Cohen (1977, 1988).

4. Measures of magnitude of treatment effect for the between-subjects factorial analysis of variance: Omega squared (Test 27g) and Cohen's f index (Test 27h) Prior to reading this section the reader should review the discussion of magnitude of treatment effect in Section VI of both the **t test for two independent samples** and the **single-factor between-subjects analysis of variance**. The discussion for the latter test notes that the computation of an omnibus F value only provides a researcher with information regarding whether the null hypothesis can be rejected — i.e., whether a significant difference exists between at least two of the experimental treatments within a given factor. An F value (as well as the level of significance with which it is associated), however, does not provide the researcher with any information regarding the size of any treatment effect that is present. As is noted in earlier discussions of treatment effect, the latter is defined as the proportion of the variability on the dependent variable that is associated with the independent variable/experimental treatments. The measures described in this section are variously referred to as **measures of effect size**, **measures of magnitude of treatment effect**, **measures of association**, and **correlation coefficients**.

Omega squared (Test 27g) The **omega squared** statistic is a commonly computed measure of treatment effect for the **between-subjects factorial analysis of variance**. Keppel (1991) and Kirk (1995) note that there is disagreement with respect to which variance components should be employed in computing **omega squared** for a factorial design. One method of computing **omega squared** (which computes a value referred to as **standard omega squared**) was employed in the previous edition of this book. The latter method expresses treatment variability for each of the factors as a proportion of the sum of all the elements that account for variability in a between-subjects factorial design (i.e., the variability for a given factor is divided by the sum of variability for all of the factors, interactions, and within-groups variability). A second method for computing **omega squared** computes what is referred to as **partial omega squared** (which was also computed in reference to the **single-factor within-subjects analysis of variance**). In computing the latter measure, which Keppel (1991) and Kirk (1995) view as more meaningful than **standard omega squared**, the proportion of variability for a given factor is divided by the sum of the proportion of variability for that factor and within-groups variability (i.e., variability attributable to other factors and interactions is ignored)

Equations 27.51–27.53, respectively, summarize the elements that are employed to compute **standard omega squared** ($\tilde{\omega}_s^2$) for Factors A and B and the AB interaction (i.e., $\tilde{\omega}_{sA}^2$, $\tilde{\omega}_{sB}^2$, and $\tilde{\omega}_{sAB}^2$ represent **standard omega squared** for Factors A and B and the AB interaction).¹⁹ Equations 27.48–27.50 represent the population parameters (ω_{sA}^2 , ω_{sB}^2 , and ω_{sAB}^2) estimated by Equations 27.51–27.53.

$$\omega_{sA}^2 = \frac{\sigma_A^2}{\sigma_A^2 + \sigma_B^2 + \sigma_{AB}^2 + \sigma_{WG}^2} \quad (\text{Equation 27.48})$$

$$\omega_{sB}^2 = \frac{\sigma_B^2}{\sigma_A^2 + \sigma_B^2 + \sigma_{AB}^2 + \sigma_{WG}^2} \quad (\text{Equation 27.49})$$

$$\omega_{sAB}^2 = \frac{\sigma_{AB}^2}{\sigma_A^2 + \sigma_B^2 + \sigma_{AB}^2 + \sigma_{WG}^2} \quad (\text{Equation 27.50})$$

$$\tilde{\omega}_{sA}^2 = \frac{\tilde{\sigma}_A^2}{\tilde{\sigma}_A^2 + \tilde{\sigma}_B^2 + \tilde{\sigma}_{AB}^2 + \tilde{\sigma}_{WG}^2} \quad (\text{Equation 27.51})$$

$$\tilde{\omega}_{sB}^2 = \frac{\tilde{\sigma}_B^2}{\tilde{\sigma}_A^2 + \tilde{\sigma}_B^2 + \tilde{\sigma}_{AB}^2 + \tilde{\sigma}_{WG}^2} \quad (\text{Equation 27.52})$$

$$\tilde{\omega}_{sAB}^2 = \frac{\tilde{\sigma}_{AB}^2}{\tilde{\sigma}_A^2 + \tilde{\sigma}_B^2 + \tilde{\sigma}_{AB}^2 + \tilde{\sigma}_{WG}^2} \quad (\text{Equation 27.53})$$

Equations 27.57–27.59, respectively, summarize the elements that are employed to compute **partial omega squared** ($\tilde{\omega}_p^2$) for Factors A and B and the AB interaction. Equations 27.54–27.56 represent the population parameters estimated by Equations 27.57–27.59.

$$\omega_{pA}^2 = \frac{\sigma_A^2}{\sigma_A^2 + \sigma_{WG}^2} \quad (\text{Equation 27.54})$$

$$\omega_{pB}^2 = \frac{\sigma_B^2}{\sigma_B^2 + \sigma_{WG}^2} \quad (\text{Equation 27.55})$$

$$\omega_{pAB}^2 = \frac{\sigma_{AB}^2}{\sigma_{AB}^2 + \sigma_{WG}^2} \quad (\text{Equation 27.56})$$

$$\tilde{\omega}_{pA}^2 = \frac{\tilde{\sigma}_A^2}{\tilde{\sigma}_A^2 + \tilde{\sigma}_{WG}^2} \quad (\text{Equation 27.57})$$

$$\tilde{\omega}_{pB}^2 = \frac{\tilde{\sigma}_B^2}{\tilde{\sigma}_B^2 + \tilde{\sigma}_{WG}^2} \quad (\text{Equation 27.58})$$

$$\tilde{\omega}_{pAB}^2 = \frac{\tilde{\sigma}_{AB}^2}{\tilde{\sigma}_{AB}^2 + \tilde{\sigma}_{WG}^2} \quad (\text{Equation 27.59})$$

Where:

$$\tilde{\sigma}_A^2 = \frac{df_A (MS_A - MS_{WG})}{npq} = \frac{(1)(84.5 - 1)}{(3)(2)(3)} = 4.64$$

$$\tilde{\sigma}_B^2 = \frac{df_B (MS_B - MS_{WG})}{npq} = \frac{(2)(26 - 1)}{(3)(2)(3)} = 2.78$$

$$\tilde{\sigma}_{AB}^2 = \frac{df_{AB} (MS_{AB} - MS_{WG})}{npq} = \frac{(2)(8 - 1)}{(3)(2)(3)} = .78$$

$$\tilde{\sigma}_{WG}^2 = MS_{WG} = 1$$

Thus:

$$\tilde{\omega}_{sA}^2 = \frac{4.64}{4.64 + 2.78 + .78 + 1} = .50$$

$$\tilde{\omega}_{sB}^2 = \frac{2.78}{4.64 + 2.78 + .78 + 1} = .30$$

$$\tilde{\omega}_{sAB}^2 = \frac{.78}{4.64 + 2.78 + .78 + 1} = .08$$

$$\tilde{\omega}_{pA}^2 = \frac{4.64}{4.64 + 1} = .82$$

$$\tilde{\omega}_{pB}^2 = \frac{2.78}{2.78 + 1} = .74$$

$$\tilde{\omega}_{pAB}^2 = \frac{.78}{.78 + 1} = .44$$

Equations 27.60–27.62 can also be employed to compute the values of **partial omega squared**.

$$\begin{aligned} \tilde{\omega}_{pA}^2 &= \frac{(p - 1)(F_A - 1)}{(p - 1)(F_A - 1) + npq} \\ &= \frac{(2 - 1)(84.5 - 1)}{(2 - 1)(84.5 - 1) + (3)(2)(3)} = .82 \end{aligned} \quad \text{(Equation 27.60)}$$

$$\begin{aligned} \tilde{\omega}_{pB}^2 &= \frac{(q - 1)(F_B - 1)}{(q - 1)(F_B - 1) + npq} \\ &= \frac{(3 - 1)(26 - 1)}{(3 - 1)(26 - 1) + (3)(2)(3)} = .74 \end{aligned} \quad \text{(Equation 27.61)}$$

$$\begin{aligned} \tilde{\omega}_{pAB}^2 &= \frac{(p - 1)(q - 1)(F_{AB} - 1)}{(p - 1)(q - 1)(F_{AB} - 1) + npq} \\ &= \frac{(2 - 1)(3 - 1)(8 - 1)}{(2 - 1)(3 - 1)(8 - 1) + (3)(2)(3)} = .44 \end{aligned} \quad \text{(Equation 27.62)}$$

The results of the above analysis for **standard omega squared** indicates that 50% of the variability on the dependent variable is associated with Factor A (Humidity), 30% with Factor B (Temperature), and 8% with the AB interaction. Thus, 50% + 30% + 8% = 88% of the variability on the dependent variable (problem-solving scores) is associated with variability on the two factors/independent variables and the interaction between them. It should be noted that although in some instances a small value for **omega squared** may indicate that the contribution of a factor or the interaction is trivial, this will not always be the case. Thus, in the example under discussion, although the value $\tilde{\omega}_{sAB}^2 = .08$ is small relative to the **omega squared** values computed for the main effects, inspection of the data clearly indicates that in order to understand the influence of temperature on problem-solving scores, it is imperative that one take into account the level of humidity, and vice versa.

The values computed for **partial omega squared** indicate that 82% of the variability on the dependent variable is associated with Factor A (Humidity), 74% with Factor B (Temperature), and 44% with the AB interaction. Note that since the value computed for **partial omega squared** for a given factor does not take into account variability on the other factors or the interaction, it yields a much higher value for that factor and the interaction than **standard omega squared** computed for the same factor and the interaction. You should also note that when **partial omega squared** is computed, the sum of the proportions/percentage values can exceed 1/100%.

It was noted in an earlier discussion of **omega squared** (in Section VI of the **t test for two independent samples**) that Cohen (1977; 1988, pp. 284–287) has suggested the following (admittedly arbitrary) values, which are employed in psychology and a number of other disciplines, as guidelines for interpreting $\tilde{\omega}^2$: a) A **small effect size** is one that is greater than .0099 but not more than .0588; b) A **medium effect size** is one that is greater than .0588 but not more than .1379; and c) A **large effect size** is greater than .1379. If one employs Cohen's (1977, 1988) guidelines for magnitude of treatment effect, all of the **omega squared** values computed in this section represent a large treatment effect, with the exception of $\tilde{\omega}_{sAB}^2 = .08$, which represents a medium effect.

Cohen's *f* index (Test 27h) If, for a given factor, the value of **partial omega squared** is substituted in Equation 21.45, **Cohen's *f* index** can be computed. In Section VI of the **single-factor between-subjects analysis of variance**, it was noted that **Cohen's *f* index** is an alternate measure of effect size that can be employed for an analysis of variance. The computation of **Cohen's *f* index** with Equation 21.45 yields the following values: $f_A = 2.13$, $f_B = 1.69$, $f_{AB} = .89$.

$$f_A = \sqrt{\frac{\tilde{\omega}_{pA}^2}{1 - \tilde{\omega}_{pA}^2}} = \sqrt{\frac{.82}{1 - .82}} = 2.13$$

$$f_B = \sqrt{\frac{\tilde{\omega}_{pB}^2}{1 - \tilde{\omega}_{pB}^2}} = \sqrt{\frac{.74}{1 - .74}} = 1.69$$

$$f_{AB} = \sqrt{\frac{\tilde{\omega}_{pAB}^2}{1 - \tilde{\omega}_{pAB}^2}} = \sqrt{\frac{.44}{1 - .44}} = .89$$

In the discussion of **Cohen's *f* index** in Section VI of the **single-factor between-subjects analysis of variance**, it was noted that Cohen (1977; 1988, pp. 284–288) employed the following

(admittedly arbitrary) f values as criteria for identifying the magnitude of an effect size: a) A **small effect size** is one that is greater than .1 but not more than .25; b) A **medium effect size** is one that is greater than .25 but not more than .4; and c) A **large effect size** is greater than .4. Employing Cohen's criteria, all of the values computed for f represent large effect sizes.

A thorough discussion of the general issues involved in computing a measure of magnitude of treatment effect for a **between-subjects factorial analysis of variance** can be found in Keppel (1991) and Kirk (1995). Further discussion of the indices of treatment effect discussed in this section, and the relationship between effect size and statistical power can be found in Section IX (the **Addendum**) of the **Pearson product-moment correlation coefficient** under the discussion of **meta-analysis and related topics**.

5. Computation of a confidence interval for the mean of a population represented by a group The same procedure employed to compute a confidence interval for a treatment population for the **single-factor between-subjects analysis of variance** can be employed with the **between-subjects factorial analysis of variance** to compute a confidence interval for the mean of any population represented by the pq groups. Although it will not be demonstrated here, the computational procedure requires that the appropriate values be substituted in Equation 21.48. In the event a researcher wants to compute a confidence interval for the mean of one of the levels of any of the factors, the number of subjects in the denominator of the radical of Equation 21.48 is based on the number of subjects who served within each level of the relevant factor (i.e., nq in the case of Factor A and np in the case of Factor B).

6. Additional analysis of variance procedures for factorial designs Section IX (the **Addendum**) provides a description of the following additional factorial analysis of variance procedures: a) **The factorial analysis of variance for a mixed design (Test 27i)**; and b) **The within-subjects factorial analysis of variance (Test 27j)**. The discussion of each of the aforementioned analysis of variance procedures includes the following: a) A description of the design for which it is employed; b) An example involving the same variables which are employed in Example 27.1; c) The computational equations for computing the appropriate F ratios; and d) Computation of the F ratios for the relevant example.

VII. Additional Discussion of the Between-Subjects Factorial Analysis of Variance

1. Theoretical rationale underlying the between-subjects factorial analysis of variance As noted in Section IV, as is the case for the **single-factor between-subjects analysis of variance**, the total variability for the **between-subjects factorial analysis of variance** can be divided into **between-groups variability** and **within-groups variability**. Although it is not required in order to compute the F ratios, the value MS_{BG} (which represents between-groups variability) can be used to represent the variance of the means of the pq groups. MS_{BG} can be computed with the equation $MS_{BG} = SS_{BG}/df_{BG}$. As noted earlier, between-groups variability is comprised of the following elements: a) **Variability attributable to Factor A** (represented by the notation MS_A), which represents the variance of the means of the p levels of Factor A; b) **Variability attributable to Factor B** (represented by the notation MS_B), which represents the variance of the means of the q levels of Factor B; and c) **Variability attributable to any interaction that is present between Factors A and B** (represented by the notation MS_{AB}), which is a measure of variance that represents whatever remains of between-groups variability after the contributions of the main effects of Factors A and B have been subtracted from between-groups variability.

In computing the three F ratios for the **between-subjects factorial analysis of variance**,

the values MS_A , MS_B , and MS_{AB} are contrasted with MS_{WG} , which serves as a baseline measure of error variability. In other words, MS_{WG} represents experimental error which results from factors that are beyond an experimenter's control. As is the case for the **single-factor between-subjects analysis of variance**, in the **between-subjects factorial analysis of variance**, MS_{WG} is the normal amount of variability that is expected between the scores of different subjects who serve under the same experimental condition. Thus, MS_{WG} represents the average of the variances computed for each of the pq groups. As long as any of the elements that comprise between-groups variability (MS_A , MS_B , or MS_{AB}) are approximately the same value as within-groups variability (MS_{WG}), the experimenter can attribute variability on a between-groups component to experimental error. When, however, any of the components that comprise between-groups variability are substantially greater than MS_{WG} , it indicates that something over and above error variability is contributing to that element of variability. In such a case it is assumed that the inflated level of variability for the between-groups component is the result of a treatment effect.

2. Definitional equations for the between-subjects factorial analysis of variance In the description of the computational protocol for the **between-subjects factorial analysis of variance** in Section IV, Equations 27.9–27.14 are employed to compute the values SS_T , SS_{BG} , SS_A , SS_B , SS_{AB} , and SS_{WG} . The latter set of computational equations were employed, since they allow for the most efficient computation of the sum of squares values. As noted in Section IV, computational equations are derived from definitional equations which reveal the underlying logic involved in the derivation of the sums of squares.

As noted previously, the total sum of squares (SS_T) can be broken down into two elements, the between-groups sum of squares (SS_{BG}) and the within-groups sum of squares (SS_{WG}). The contribution of any single subject's score to the total variability in the data can be expressed in terms of a between-groups component and a within-groups component. When the between-groups component and the within-groups component are added, the sum reflects that subject's total contribution to the overall variability in the data. Furthermore, the between-groups sum of squares can be broken down into three elements: a sum of squares for Factor A (SS_A), a sum of squares for Factor B (SS_B), and an interaction sum of squares (SS_{AB}). The contribution of any single subject's score to between-groups variability in the data can be expressed in terms of an A, a B, and an AB component. When the A, B, and AB components for a given subject are added, the sum reflects that subject's total contribution to between-groups variability in the data. The aforementioned information is reflected in the definitional equations which will now be described for computing the sums of squares.

Equation 27.63 is the definitional equation for the **total sum of squares**.²⁰ In Equation 27.63 the notation X_{ijk} is employed to represent the score of the i^{th} subject in the group that serves under Level j of Factor A and Level k of Factor B.²¹ When the notation $\sum_{k=1}^q \sum_{j=1}^p \sum_{i=1}^n$ precedes a term in parentheses, it indicates that the designated operation should be carried out for all $N = npq$ subjects.²²

$$SS_T = \sum_{k=1}^q \sum_{j=1}^p \sum_{i=1}^n (X_{ijk} - \bar{X}_T)^2 \quad \text{(Equation 27.63)}$$

In employing Equation 27.63 to compute SS_T , the grand mean (\bar{X}_T) is subtracted from each of the $N = npq$ scores and each of the N difference scores is squared. The total sum of squares (SS_T) is the sum of the N squared difference scores. Equation 27.63 is computationally equivalent to Equation 27.9.

Equation 27.64 is the definitional equation for the **between-groups sum of squares**.

$$SS_{BG} = n \sum_{k=1}^q \sum_{j=1}^p (\bar{X}_{AB_{jk}} - \bar{X}_T)^2 \quad (\text{Equation 27.64})$$

In employing Equation 27.64 to compute SS_{BG} , the following operations are carried out for each of the pq groups. The grand mean (\bar{X}_T) is subtracted from the group mean ($\bar{X}_{AB_{jk}}$). The difference score is squared, and the squared difference score is multiplied by the number of subjects in the group (n). After this is done for all pq groups, the values that have been obtained for each group as a result of multiplying the squared difference score by the number of subjects in a group are summed. The resulting value represents the between-groups sum of squares (SS_{BG}). Equation 27.64 is computationally equivalent to Equation 27.10.

Equation 27.65 is the definitional equation for the **sum of squares for Factor A**.

$$SS_A = nq \sum_{j=1}^p (\bar{X}_{A_j} - \bar{X}_T)^2 \quad (\text{Equation 27.65})$$

In employing Equation 27.65 to compute SS_A , the following operations are carried out for each of the p levels of Factor A. The grand mean (\bar{X}_T) is subtracted from the mean of that level of Factor A (\bar{X}_{A_j}). The difference score is squared, and the squared difference score is multiplied by the number of subjects in the level ($n_{A_j} = nq$). After this is done for all p levels of Factor A, the values that have been obtained for each level as a result of multiplying the squared difference score by the number of subjects in a level are summed. The resulting value represents the sum of squares for Factor A (SS_A). Equation 27.65 is computationally equivalent to Equation 27.11.

Equation 27.66 is the definitional equation for the **sum of squares for Factor B**.

$$SS_B = np \sum_{k=1}^q (\bar{X}_{B_k} - \bar{X}_T)^2 \quad (\text{Equation 27.66})$$

In employing Equation 27.66 to compute SS_B , the following operations are carried out for each of the q levels of Factor B. The grand mean (\bar{X}_T) is subtracted from the mean of that level of Factor B (\bar{X}_{B_k}). The difference score is squared, and the squared difference score is multiplied by the number of subjects in the level ($n_{B_k} = np$). After this is done for all q levels of Factor B, the values that have been obtained for each level as a result of multiplying the squared difference score by the number of subjects in a level are summed. The resulting value represents the sum of squares for Factor B (SS_B). Equation 27.66 is computationally equivalent to Equation 27.12.

Equation 27.67 is the definitional equation for the **interaction sum of squares**.

$$SS_{AB} = n \sum_{k=1}^q \sum_{j=1}^p (\bar{X}_{AB_{jk}} - \bar{X}_{A_j} - \bar{X}_{B_k} + \bar{X}_T)^2 \quad (\text{Equation 27.67})$$

In employing Equation 27.67 to compute SS_{AB} , the following operations are carried out for each of the pq groups. The mean of the level of Factor A the group represents (\bar{X}_{A_j}) and the mean of the level of Factor B the group represents (\bar{X}_{B_k}) are subtracted from the mean of the group ($\bar{X}_{AB_{jk}}$), and the grand mean (\bar{X}_T) is added to the resulting value. The result of the aforementioned operation is squared, and the squared difference score is multiplied by the number of subjects in that group ($n = n_{AB_{jk}}$). After this is done for all pq groups, the values that have been obtained for each group are summed, and the resulting value represents the sum of

squares for the interaction (SS_{AB}).²³ Equation 27.67 is computationally equivalent to Equation 27.13.

Equation 27.68 is the definitional equation for the **within-groups sum of squares**.

$$SS_{WG} = \sum_{k=1}^q \sum_{j=1}^p \sum_{i=1}^n (X_{ijk} - \bar{X}_{AB_{jk}})^2 \quad (\text{Equation 27.68})$$

In employing Equation 27.68 to compute SS_{WG} , the following operations are carried out for each of the pq groups. The group mean ($\bar{X}_{AB_{jk}}$) is subtracted from each score in the group. The difference scores are squared, after which the sum of the squared difference scores is obtained. The sum of the sum of the squared difference scores for all pq groups represents the within-groups sum of squares. Equation 27.68 is computationally equivalent to Equation 27.14.

3. Unequal sample sizes The equations presented in this book for the **between-subjects factorial analysis of variance** assume there is an equal number of subjects in each of the pq groups (i.e., the value of $n_{AB_{jk}}$ is equal for each group). When the number of subjects per group is not equal, most sources recommend that adjusted sum of squares and sample size values be employed in conducting the analysis of variance. One approach to dealing with unequal sample sizes, which is generally referred to as the **unweighted means procedure**, employs the harmonic mean of the sample sizes of the pq groups to represent the value of $n = n_{AB_{jk}}$.²⁴ Based on the computed value of the harmonic mean (which will be designated \bar{n}_h), the sample size of each row and column, as well as the total sample size are adjusted as follows: $n_{A_j} = (\bar{n}_h)(q)$, $n_{B_k} = (\bar{n}_h)(p)$, $N = (\bar{n}_h)(p)(q)$. In addition, the $\sum X_{AB_{jk}}$ score of each group is adjusted by multiplying the mean of the group derived from the original data by the value computed for the harmonic mean (i.e., $(\bar{X}_{AB_{jk}})(\bar{n}_h) = \text{Adjusted value of } \sum X_{AB_{jk}}$). Employing the adjusted $\sum X_{AB_{jk}}$ values, the value of $\sum X_T$ and the values of the sums of the rows ($\sum X_{A_j}$) and columns ($\sum X_{B_k}$) are adjusted accordingly. The adjusted values of $\sum X_T$, $\sum X_{AB_{jk}}$, $\sum X_{A_j}$, $\sum X_{B_k}$, $n_{AB_{jk}}$, n_{A_j} , n_{B_k} , and N , are substituted in Equations 27.9–27.13 to compute the values SS_T , SS_{BG} , SS_A , SS_B , and SS_{AB} . The value of SS_{WG} , on the other hand, is a pooled within-groups sum of squares that is based on the original unadjusted data. Thus, employing the original unadjusted values of $\sum X_{AB_{jk}}$ and $n_{AB_{jk}}$, the sum of squares is computed for each of the pq groups employing the following equation: $\sum X_{AB_{jk}}^2 - [(\sum X_{AB_{jk}})^2/n_{AB_{jk}}]$. The sum of the pq sum of squares values represents the pooled within-groups sum of squares. This latter value is, in fact, computed in Endnote 4. The values MS_A , MS_B , and MS_{AB} are computed with Equations 27.15–27.17, by dividing the relevant sum of squares value by the appropriate degrees of freedom. The degrees of freedom for the aforementioned mean square values are computed with Equations 27.19–27.21. Although the value MS_{WG} is computed with Equation 27.18, the value df_{WG} in the denominator of Equation 27.18 is a pooled within-groups degrees of freedom. The latter degrees of freedom value is determined by computing the value $(n_{AB_{jk}} - 1)$ for each group, and summing the $(n_{AB_{jk}} - 1)$ values for each of the pq groups. When the resulting degrees of freedom value is divided into the pooled within-groups sum of squares, it yields the value MS_{WG} that is employed in computing the F ratios. Equations 27.25–27.27 are employed to compute the values F_A , F_B , and F_{AB} . Keppel (1991) notes that since the F values derived by the method described in this section may underestimate the likelihood of committing a Type I error, it is probably prudent to employ a lower tabled probability to represent the prespecified level of significance — i.e., employ the tabled critical $F_{.01}$ value to represent the tabled critical $F_{.05}$ value. Alternative methods for dealing with unequal sample sizes are described in Keppel (1991), Kirk (1982, 1995), and Winer *et al.* (1991).

4. Final comments on the between-subjects factorial analysis of variance

a) **Fixed-effects versus random-effects versus mixed-effects models** In Section VII of the **single-factor between-subjects analysis of variance** it is noted that one assumption underlying the analysis of variance is whether or not the levels of an independent variable are **fixed** or **random**. Whereas a **fixed-effects model** assumes that the levels of an independent variable are the same levels that will be employed in any attempted replication of the experiment, a **random-effects model** assumes that the levels have been randomly selected from the overall population of all possible levels that can be employed for the independent variable. The computational procedures for all of the analysis of variance procedures described in this book assume a fixed-effects model for all factors.

In the case of factorial designs it is also possible to have a **mixed-effects model**, which is a combination of a fixed-effects and a random-effects model. Specifically, in the case of a two-factor design, a mixed-effects model assumes that one of the factors is based on a fixed-effects model while the second factor is based on a random-effects model. When there are three or more factors, a mixed-effects model assumes that one or more of the factors is based on a fixed-effects model and one or more of the factors is based on a random-effects model. Texts that specialize in the analysis of variance provide in-depth discussions of this general subject, as well as describing the modified equations that are appropriate for evaluating factorial designs that are based on random- and mixed-effects models.

b) **Nested factors/hierarchical designs and designs involving more than two factors** In designing experiments that involve two or more factors, it is possible to employ what are referred to as **nested factors**. Nesting is present in an experimental design when different levels of one factor do not occur at all levels of another factor. To illustrate nesting, let us assume that a researcher wants to evaluate two teaching methods (which will comprise Factor A) in 10 different classes, each of which is unique with respect to the ethnic makeup of its students. The 10 different classes will comprise Factor B. Five of the classes ($B_1 \dots B_5$) are taught by teaching method A_1 and the other five classes ($B_6 \dots B_{10}$) by teaching method A_2 . In such a case Factor B is nested under Factor A, since each level of Factor B serves under only one level of Factor A. Figure 27.3 outlines the design.²⁵



Figure 27.3 Example of a Nested Design

Winer *et al.* (1991) note that in the above described design it is not possible to evaluate whether there is an interaction between the two factors. The reason for this is that in order to test for an interaction, it is necessary that all levels of Factor B must occur under all of the levels of Factor A. When the latter is true (as is the case in Example 27.1), the two factors are said to be **crossed**. The term **hierarchical design** is often employed to describe designs in which there are two or more nested factors. It is also possible to have a **partially hierarchical design**, in which at least one factor is nested and at least one factor is crossed. Since the statistical model upon which nested designs are based differs from the model that has been employed for the **between-subjects factorial analysis of variance**, the analysis of such designs requires the use of different equations.

As noted earlier, a **between-subjects factorial analysis of variance** (as well as a **factorial analysis of variance for a mixed design** and a **within-subjects factorial analysis of variance** discussed in Section IX) can involve more than two factors. To further complicate matters,

designs with three or more factors can involve some factors that are nested and others that are crossed, plus the fact that a fixed-effects model may be assumed for some factors and a random-effects model for others. Honeck *et al.* (1983) is an excellent source for deriving the appropriate equations for the use of the analysis of variance with experimental designs involving nesting and/or the use of more than two factors. Other sources on this subject are Keppel (1991), Kirk (1982, 1995), and Winer *et al.* (1991).

VIII. Additional Examples Illustrating the Use of the Between-Subjects Factorial Analysis of Variance

Examples 27.2 and 27.3 are two additional examples that can be evaluated with the **between-subjects factorial analysis of variance**. Since the data for both examples are identical to that employed in Example 27.1, they yield the same result. Note that whereas in Example 27.1 both Factor A and Factor B are manipulated independent variables, in Example 27.2 Factor B is manipulated while Factor A is nonmanipulated (i.e., is a subject/attribute independent variable). In Example 27.3 both factors are nonmanipulated independent variables.

Example 27.2 *A study is conducted in order to evaluate the impact of gender (to be designated as Factor A) and anxiety level (to be designated as Factor B) on affiliation. The experimenter employs a 2×3 between-subjects (completely-randomized) factorial design. The two levels that comprise Factor A are A_1 : Male; A_2 : Female. The three levels that comprise Factor B are B_1 : Low Anxiety; B_2 : Moderate Anxiety; B_3 : High Anxiety. Each of nine males and nine females is randomly assigned to one of three experimental conditions. All of the subjects are told they are participants in a learning experiment which will require them to learn lists of words. Subjects in the low anxiety condition are told that there will be no consequences for poor performance in the experiment. Subjects in the moderate anxiety condition are told if they perform below a certain level they will have to drink a distasteful beverage. Subjects in the high anxiety condition are told if they perform below a certain level they will be given a painful electric shock. All subjects are told that while waiting to be tested they can either wait by themselves or with other people. Each subject is asked to designate the number of people he or she would like in the room with him or her while waiting to be tested. This latter measure is employed to represent the dependent variable of affiliation. The experimenter assumes that the higher a subject is in affiliation, the more people the subject will want to be with while waiting. The affiliation scores of the three subjects in each of the six experimental groups/conditions (which result from the combinations of the levels that comprise the two factors) follow: **Group AB_{11}** : Male/Low anxiety (11, 9, 10); **Group AB_{12}** : Male/Moderate anxiety (7, 8, 6); **Group AB_{13}** : Male/High anxiety (5, 4, 3); **Group AB_{21}** : Female/Low anxiety (2, 4, 3); **Group AB_{22}** : Female/Moderate anxiety (4, 5, 3); **Group AB_{23}** : Female/High anxiety (0, 1, 2). Do the data indicate that either gender or anxiety level influence affiliation?*

Example 27.3 *A study is conducted in order to evaluate if there is a relationship between ethnicity (to be designated as Factor A) and socioeconomic class (to be designated as Factor B), and the number of times a year a person visits a doctor. The experimenter employs a 2×3 between-subjects (completely-randomized) factorial design. The two levels that comprise Factor A are A_1 : Caucasian; A_2 : Afro-American. The three levels that comprise Factor B are B_1 : Lower socioeconomic class; B_2 : Middle socioeconomic class; B_3 : Upper socioeconomic class. Based on their occupation and income, each of nine Caucasians and nine Afro-Americans is categorized with respect to whether he or she is a member of the lower, middle, or upper socioeconomic class. Upon doing this the experimenter determines the number of times during*

the past year each of the subjects has visited a doctor. This latter measure represents the dependent variable in the study. The number of visits for the three subjects in each of the six experimental groups/conditions (which result from the combinations of the levels that comprise the two factors) follow: **Group AB₁₁**: Caucasian/Lower socioeconomic class (11, 9, 10); **Group AB₁₂**: Caucasian/Middle socioeconomic class (7, 8, 6); **Group AB₁₃**: Caucasian/Upper socioeconomic class (5, 4, 3); **Group AB₂₁**: Afro-American/Lower socioeconomic class (2, 4, 3); **Group AB₂₂**: Afro-American/Middle socioeconomic class (4, 5, 3); **Group AB₂₃**: Afro-American/Upper socioeconomic class (0, 1, 2). Do the data indicate that either ethnicity or socioeconomic class is related to how often a person visits a doctor?

IX. Addendum

Discussion of additional analysis of variance procedures for factorial designs

1. Test 27i: The factorial analysis of variance for a mixed design A mixed factorial design involves two or more independent variables/factors in which at least one of independent variables is measured between-subjects (different subjects serve under each of the levels of that independent variable) and at least one of the independent variables is measured within-subjects (the same subjects or matched sets of subjects serve under all of the levels of that independent variable). Although the **factorial analysis of variance for a mixed design** can be used with designs involving more than two factors, the computational protocol to be described in this section will be limited to the two-factor experiment. For purposes of illustration it will be assumed that Factor A is measured between-subjects (i.e., different subjects serve in each of the p levels of Factor A), and that Factor B is measured within-subjects (i.e., all subjects are measured on each of the q levels of Factor B). Since one of the factors is measured within-subjects, a **mixed factorial design** requires a fraction of the subjects that are needed to evaluate the same set of hypotheses with a **between-subjects factorial design** (assuming both designs employ the same number of scores in each of the pq experimental conditions). To be more specific, the fraction of subjects required is 1 divided by the number of levels of the within-subjects factor (i.e., $1/q$ if Factor B is the within-subjects factor). The advantages as well as the disadvantages of a within-subjects analysis (which are discussed under the **t test for two dependent samples** and the **single-factor within-subjects analysis of variance**) also apply to the within-subjects factor that is evaluated with the **factorial analysis of variance for a mixed design**. Probably the most notable advantage associated with the within-subjects factor is that it allows for a more powerful test of an alternative hypothesis when contrasted with the between-subjects factor. Example 27.4 is employed to illustrate the use of the **factorial analysis of variance for a mixed design**.

Example 27.4 A study is conducted to evaluate the effect of humidity (to be designated as Factor A) and temperature (to be designated as Factor B) on mechanical problem-solving ability. The experimenter employs a 2×3 mixed factorial design. The two levels that comprise Factor A are A_1 : Low humidity; A_2 : High humidity. The three levels that comprise Factor B are B_1 : Low temperature; B_2 : Moderate temperature; B_3 : High temperature. The study employs six subjects, three of whom are randomly assigned to Level 1 of Factor A and three of whom are randomly assigned to Level 2 of Factor A. Each subject is exposed to all three levels of Factor B. The order of presentation of the levels of Factor B is completely counterbalanced within the six subjects. The number of mechanical problems solved by the subjects in the six experimental conditions (which result from combinations of the levels of the two factors) follow: **Condition AB₁₁**: Low humidity/Low temperature (11, 9, 10); **Condition AB₁₂**: Low humidity/Moderate temperature (7, 8, 6); **Condition AB₁₃**: Low humidity/High temperature (5, 4, 3);

Condition AB_{21} : High humidity/Low temperature (2, 4, 3); **Condition AB_{22} :** High humidity/Moderate temperature (4, 5, 3); **Condition AB_{23} :** High humidity/High temperature (0, 1, 2). Do the data indicate that either humidity or temperature influences mechanical problem-solving ability?

The data for Example 27.4 are summarized in Table 27.7.

Table 27.7 Data for Example 27.4 for Evaluation with the Factorial Analysis of Variance for a Mixed Design

	A_1			Subject sums ($\sum S_i$)
	B_1	B_2	B_3	
Subject 1	11	7	5	$\sum S_1 = 23$
Subject 2	9	8	4	$\sum S_2 = 21$
Subject 3	10	6	3	$\sum S_3 = 19$
Condition sums	$\sum X_{AB_{11}} = 30$ $\sum X_{AB_{11}}^2 = 302$	$\sum X_{AB_{12}} = 21$ $\sum X_{AB_{12}}^2 = 149$	$\sum X_{AB_{13}} = 12$ $\sum X_{AB_{13}}^2 = 50$	$\sum X_{A_1} = 63$
	A_2			Subject sums ($\sum S_i$)
	B_1	B_2	B_3	
Subject 4	2	4	0	$\sum S_4 = 6$
Subject 5	4	5	1	$\sum S_5 = 10$
Subject 6	3	3	2	$\sum S_6 = 8$
Condition sums	$\sum X_{AB_{21}} = 9$ $\sum X_{AB_{21}}^2 = 29$	$\sum X_{AB_{22}} = 12$ $\sum X_{AB_{22}}^2 = 50$	$\sum X_{AB_{23}} = 3$ $\sum X_{AB_{23}}^2 = 5$	$\sum X_{A_2} = 24$
	$\sum X_{B_1} = 39$	$\sum X_{B_2} = 33$	$\sum X_{B_3} = 15$	$\sum X_T = 87$ $\sum X_T^2 = 585$

Examination of Table 27.7 reveals that since the data employed for Example 27.4 are identical to that employed for Example 27.1, the summary values for the rows, columns, and pq experimental conditions are identical to those in Table 27.1. Thus, the following values in Table 27.7 are identical to those obtained in Table 27.1: $n_{A_j} = 9$ and the values computed for $\sum X_{A_j}$ and $\sum X_{A_j}^2$ for each of the levels of Factor A; $n_{B_k} = 6$ and the values computed for $\sum X_{B_k}$ and $\sum X_{B_k}^2$ for each of the levels of Factor B; $n_{AB_{jk}} = n = 3$ and the values computed for $\sum X_{AB_{jk}}$ and $\sum X_{AB_{jk}}^2$ for each of the pq experimental conditions that result from combinations of the levels of the two factors; $N = npq = 18$; $\sum X_T = 87$; $\sum X_T^2 = 585$.

Note that in both the **between-subjects factorial analysis of variance** and the **factorial analysis of variance for a mixed design**, the value $n_{AB_{jk}} = n = 3$ represents the number of scores in each of the pq experimental conditions. In the case of the **factorial analysis of variance for a mixed design**, the value $N = npq = 18$ represents the total number of scores in the set of data. Note, however, that the latter value does not represent the total number of subjects employed in the study, as it does in the case of the **between-subjects factorial analysis of variance**. The number of subjects employed for a **factorial analysis of variance for a mixed design** will always be the value of n multiplied by the number of levels of the between-subjects factor. Thus, in Example 27.4 the number of subjects is $np = (3)(2) = 6$.²⁶

As is the case for the **between-subjects factorial analysis of variance**, the following three F ratios are computed for the **factorial analysis of variance for a mixed design**: F_A , F_B , F_{AB} . The equations required for computing the F ratios are summarized in Table 27.8. Table 27.9 summarizes the computations for the **factorial analysis of variance for a mixed design** when it is employed to evaluate Example 27.4. In order to compute the F ratios for the **factorial analysis of variance for a mixed design**, it is required that the following summary values (which are also computed for the **between-subjects factorial analysis of variance**) be computed: $[XS]$, $[T]$, $[A]$, $[B]$, and $[AB]$. Since the summary values computed in Table 27.7 are identical to those computed in Table 27.1 (for Example 27.1), the same summary values are employed in Tables 27.8 and 27.9 to compute the values $[XS]$, $[T]$, $[A]$, $[B]$, and $[AB]$ (which are, respectively, computed with Equations 27.4–27.8). Thus: $[XS] = 585$, $[T] = 420.5$, $[A] = 505$, $[B] = 472.5$, and $[AB] = 573$. Since the same set of data and the same equations are employed for the **factorial analysis of variance for a mixed design** and the **between-subjects factorial analysis of variance**, both analysis of variance procedures yield identical values for $[XS]$, $[T]$, $[A]$, $[B]$, and $[AB]$. Inspection of Table 27.8 also reveals that the **factorial analysis of variance for a mixed design** and the **between-subjects factorial analysis of variance** employ the same equations to compute the values SS_A , SS_B , SS_{AB} , SS_T , MS_A , MS_B , and MS_{AB} .

In order to compute a number of additional sum of squares values for the **factorial analysis of variance for a mixed design**, it is necessary to compute the element $[AS]$ (which is not computed for the **between-subjects factorial analysis of variance**). $[AS]$, which is computed with Equation 27.69, is employed in Tables 27.8 and 27.9 to compute the following values: $SS_{\text{Between-subjects}}$, $SS_{\text{Subjects WG}}$, $SS_{\text{Within-subjects}}$, $SS_B \times \text{subjects WG}$.

$$[AS] = \sum_{i=1}^{np} \left[\frac{(\sum S_i)^2}{q} \right] \quad (\text{Equation 27.69})$$

The notation $\sum_{i=1}^{np} [(\sum S_i)^2 / q]$ in Equation 27.69 indicates that for each of the $np = 6$ subjects, the score of the subject is squared and divided by q . The resulting values obtained for the np subjects are summed, yielding the value $[AS]$. Employing Equation 27.69, the value $[AS] = 510.33$ is computed.

$$[AS] = \frac{(23)^2}{3} + \frac{(21)^2}{3} + \frac{(19)^2}{3} + \frac{(6)^2}{3} + \frac{(10)^2}{3} + \frac{(8)^2}{3} = 510.33$$

The reader should take note of the following relationships in Tables 27.8 and 27.9:

$$SS_{\text{Between-subjects}} = SS_A + SS_{\text{Subjects WG}}$$

$$SS_{\text{Within-subjects}} = SS_B + SS_{AB} + SS_B \times \text{subjects WG}$$

$$SS_T = SS_{\text{Between-subjects}} + SS_{\text{Within-subjects}}$$

$$df_{\text{Between-subjects}} = df_A + df_{\text{Subjects WG}}$$

$$df_{\text{Within-subjects}} = df_B + df_{AB} + df_{B \times \text{subjects WG}}$$

$$df_T = df_{\text{Between-subjects}} + df_{\text{Within-subjects}}$$

**Table 27.8 Summary Table of Equations for the Factorial Analysis
of Variance for a Mixed Design**

Source of variation	SS	df	MS	F
Between-subjects	$[AS] - [T]$	$np - 1$		
A	$[A] - [T]$	$p - 1$	$\frac{SS_A}{df_A}$	$F_A = \frac{MS_A}{MS_{\text{Subjects WG}}}$
Subjects WG	$[AS] - [A]$	$p(n - 1)$	$\frac{SS_{\text{Subjects WG}}}{df_{\text{Subjects WG}}}$	
Within-subjects	$[XS] - [AS]$	$np(q - 1)$		
B	$[B] - [T]$	$q - 1$	$\frac{SS_B}{df_B}$	$F_B = \frac{MS_B}{MS_{B \times \text{subjects WG}}}$
AB	$[AB] - [A] - [B] + [T]$	$(p - 1)(q - 1)$	$\frac{SS_{AB}}{df_{AB}}$	$F_{AB} = \frac{MS_{AB}}{MS_{B \times \text{subjects WG}}}$
B × subjects WG	$[XS] - [AB] - [AS] + [A]$	$p(q - 1)(n - 1)$	$\frac{SS_{B \times \text{subjects WG}}}{df_{B \times \text{subjects WG}}}$	
Total	$[XS] - [T]$	$N - 1 = npq - 1$		

Table 27.9 Summary Table of Computations for Example 27.4

Source of variation	SS	df	MS	F
Between-subjects	$510.33 - 420.5 = 89.83$	$(3)(2) - 1 = 5$		
A	$505 - 420.5 = 84.5$	$2 - 1 = 1$	$MS_A = \frac{84.5}{1} = 84.5$	$F_A = \frac{84.5}{1.33} = 63.53$
Subjects WG	$510.33 - 505 = 5.33$	$2(3 - 1) = 4$	$MS_{\text{Subjects WG}} = \frac{5.33}{4} = 1.33$	
Within-subjects	$585 - 510.33 = 74.67$	$(3)(2)(3 - 1) = 12$		
B	$472.5 - 420.5 = 52$	$3 - 1 = 2$	$MS_B = \frac{52}{2} = 26$	$F_B = \frac{26}{.83} = 31.33$
AB	$573 - 505 - 472.5 + 420.5 = 16$	$(2 - 1)(3 - 1) = 2$	$MS_{AB} = \frac{16}{2} = 8$	$F_{AB} = \frac{8}{.83} = 9.64$
B × subjects WG	$585 - 573 - 510.33 + 505 = 6.67$	$2(3 - 1)(3 - 1) = 8$	$MS_{B \times \text{subjects WG}} = \frac{6.67}{8} = .83$	
Total	$585 - 420.5 = 164.5$	$18 - 1 = (3)(2)(3) - 1 = 17$		

Inspection of Table 27.2 and Tables 27.8/27.9 reveals that if a **between-subjects factorial analysis of variance** and a **factorial analysis of variance for a mixed design** are employed with the same set of data, identical values are computed for the following: SS_A , SS_B , SS_{AB} , SS_T , df_A , df_B , df_{AB} , df_T , MS_A , MS_B , and MS_{AB} .

In Table 27.9 the error term $MS_{\text{Subjects WG}} = 1.33$ (employed in computing the value $F_A = 63.53$) is identical to the value MS_{WG} which would be obtained if Factor B was not taken into account in Example 27.4, and the data on Factor A were evaluated with a **single-factor between-subjects analysis of variance**. The error term $MS_{B \times \text{subjects WG}} = .83$, employed in computing the values $F_B = 31.33$ and $F_{AB} = 9.64$ is analogous to the error term employed for the **single-factor within-subjects analysis of variance**. For a thorough discussion of the derivation of the error terms for the **factorial analysis of variance for a mixed design**, the reader should consult books that discuss analysis of variance procedures in greater detail (e.g., Keppel (1991) and Winer *et al.* (1991)).

The following tabled critical values derived from Table A10 are employed in evaluating the three F ratios computed for Example 27.4: a) **Factor A**: For $df_{\text{num}} = df_A = 1$ and $df_{\text{den}} = df_{\text{Subjects WG}} = 4$, $F_{.05} = 7.71$ and $F_{.01} = 21.20$; b) **Factor B**: For $df_{\text{num}} = df_B = 2$ and $df_{\text{den}} = df_{B \times \text{subjects WG}} = 8$, $F_{.05} = 4.46$ and $F_{.01} = 8.65$; and c) **AB interaction**: For $df_{\text{num}} = df_{AB} = 2$ and $df_{\text{den}} = df_{B \times \text{subjects WG}} = 8$, $F_{.05} = 4.46$ and $F_{.01} = 8.65$.

The identical null and alternative hypotheses that are evaluated in Section III of the **between-subjects factorial analysis of variance** are evaluated in the **factorial analysis of variance for a mixed design**. In order to reject the null hypothesis in reference to a computed F ratio, the obtained F value must be equal to or greater than the tabled critical value at the prespecified level of significance. Since the computed value $F_A = 63.53$ is greater than $F_{.05} = 7.71$ and $F_{.01} = 21.20$, the alternative hypothesis for Factor A is supported at both the .05 and .01 levels. Since the computed value $F_B = 31.33$ is greater than $F_{.05} = 4.46$ and $F_{.01} = 8.65$, the alternative hypothesis for Factor B is supported at both the .05 and .01 levels. Since the computed value $F_{AB} = 9.64$ is greater than $F_{.05} = 4.46$ and $F_{.01} = 8.65$, the alternative hypothesis for an interaction between Factors A and B is supported at both the .05 and .01 levels.

The analysis of the data for Example 27.4 allows the researcher to conclude that both humidity (Factor A) and temperature (Factor B) have a significant impact on problem-solving scores. However, as is the case when the same set of data is evaluated with a **between-subjects factorial analysis of variance**, the relationships depicted by the main effects must be qualified because of the presence of a significant interaction. Although the comparison procedures following the computation of the omnibus F ratios (as well as the other analytical procedures for determining power, effect size, etc.) described in Section VI of the **between-subjects factorial analysis of variance** can be extended to the **factorial analysis of variance for a mixed design**, they will not be described in this book. For a full description of such procedures, the reader should consult texts that discuss analysis of variance procedures in greater detail (e.g., Keppel (1991) and Winer *et al.* (1991)).

2. Test 27j: The within-subjects factorial analysis of variance A **within-subjects factorial design** involves two or more factors, and all subjects are measured on each of the levels of all of the factors. The **within-subjects factorial analysis of variance** (also known as a **repeated-measures factorial analysis of variance**) is an extension of the **single-factor within-subjects analysis of variance** to experiments involving two or more independent variables/factors. Although the **within-subjects factorial analysis of variance** can be used with designs involving more than two factors, the computational protocol to be described in this section will be limited to the two-factor experiment. Within the framework of the **within-subjects factorial design**, each subject contributes pq scores (which result from the combinations of the levels that comprise

the two factors). Since subjects serve under all pq experimental conditions, a **within-subjects factorial design** requires a fraction of the subjects that are needed to evaluate the same set of hypotheses with either the **between-subjects factorial design** or the **mixed factorial design** (assuming a given design employs the same number of scores in each of the pq experimental conditions). To be more specific, only $1/pq^{th}$ of the subjects are required for a **within-subjects factorial design** in contrast to a **between-subjects factorial design**. The requirement of fewer subjects, and the fact that a within-subjects analysis provides for a more powerful test of an alternative hypothesis than a between-subjects analysis, must to be weighed against the fact that it is often impractical or impossible to have subjects serve in multiple experimental conditions. In addition, a within-subjects analysis of variance is more sensitive to violations of its assumptions than a between-subjects analysis of variance. Example 27.5 is employed to illustrate the **within-subjects factorial analysis of variance**.

Example 27.5 *A study is conducted to evaluate the effect of humidity (to be designated as Factor A) and temperature (to be designated as Factor B) on mechanical problem-solving ability. The experimenter employs a 2×3 within-subjects factorial design. The two levels that comprise Factor A are A_1 : Low humidity; A_2 : High humidity. The three levels that comprise Factor B are B_1 : Low temperature; B_2 : Moderate temperature; B_3 : High temperature. The study employs three subjects, all of whom serve under the two levels of Factor A and the three levels of Factor B. The order of presentation of the combinations of the two factors is incompletely counterbalanced.²⁷ The number of mechanical problems solved by the subjects in the six experimental conditions (which result from combinations of the levels of the two factors) follow: **Condition AB_{11}** : Low humidity/Low temperature (11, 9, 10); **Condition AB_{12}** : Low humidity/Moderate temperature (7, 8, 6); **Condition AB_{13}** : Low humidity/High temperature (5, 4, 3); **Condition AB_{21}** : High humidity/Low temperature (2, 4, 3); **Condition AB_{22}** : High humidity/Moderate temperature (4, 5, 3); **Condition AB_{23}** : High humidity/High temperature (0, 1, 2). Do the data indicate that either humidity or temperature influences mechanical problem-solving ability?*

The data for Example 27.5 are summarized in Tables 27.10–27.12. In Table 27.11, $S_{i_{A_j}}$ represents the score of Subject i under Level j of Factor A. In Table 27.12, $S_{i_{B_k}}$ represents the score of Subject i under Level k of Factor B.

Examination of Tables 27.10–27.12 reveals that since the data employed for Example 27.5 are identical to that employed for Examples 27.1 and 27.4, the summary values for the rows, columns, and pq experimental conditions are identical to those in Tables 27.1 and 27.7. Thus, the following values in Tables 27.10–27.12 are identical to those obtained in the tables for Examples 27.1 and 27.4: $n_{A_j} = 9$ and the values computed for $\sum X_{A_j}$ and $\sum X_{A_j}^2$ for each of the levels of Factor A; $n_{B_k} = 6$ and the values computed for $\sum X_{B_k}$ and $\sum X_{B_k}^2$ for each of the levels of Factor B; $n_{AB_{jk}} = n = 3$ and the values computed for $\sum X_{AB_{jk}}$ and $\sum X_{AB_{jk}}^2$ for each of the pq experimental conditions that result from combinations of the levels of the two factors; $N = npq = 18$; $\sum X_T = 87$; $\sum X_T^2 = 585$.

Note that in the **within-subjects factorial analysis of variance**, the **between-subjects factorial analysis of variance**, and the **factorial analysis of variance for a mixed design**, the value $n_{AB_{jk}} = n = 3$ represents the number of scores in each of the pq experimental conditions. In the case of the **within-subjects factorial analysis of variance**, the value $N = npq = 18$ represents the total number of scores in the set of data. Note, however, that the latter value does not represent the total number of subjects employed in the study as it does in the case of the **between-subjects factorial analysis of variance**. The number of subjects employed for a

within-subjects factorial analysis of variance will always be the value of $n = n_{AB_{jk}}$. Thus, in Example 27.5 the number of subjects is $n = n_{AB_{jk}} = 3$.

Table 27.10 Data for Example 27.5 for Evaluation with the Within-Subjects Factorial Analysis of Variance

	A_1			A_2			Subject sums ($\sum S_i$)
	B_1	B_2	B_3	B_1	B_2	B_3	
Subject 1	11	7	5	2	4	0	$\sum S_1 = 29$
Subject 2	9	8	4	4	5	1	$\sum S_2 = 31$
Subject 3	10	6	3	3	3	2	$\sum S_3 = 27$
Condition	$\sum X_{AB_{11}} = 30$	$\sum X_{AB_{12}} = 21$	$\sum X_{AB_{13}} = 12$	$\sum X_{AB_{21}} = 9$	$\sum X_{AB_{22}} = 12$	$\sum X_{AB_{23}} = 3$	$\sum X_T = 87$
Sums	$\sum X_{AB_{11}}^2 = 302$	$\sum X_{AB_{12}}^2 = 149$	$\sum X_{AB_{13}}^2 = 50$	$\sum X_{AB_{21}}^2 = 29$	$\sum X_{AB_{22}}^2 = 50$	$\sum X_{AB_{23}}^2 = 5$	$\sum X_T^2 = 585$

Table 27.11 Scores of Subjects on Levels of Factor A for Example 27.5

	A_1	A_2	Subject sums ($\sum S_i$)
Subject 1	$S_{1_{A_1}} = 23$	$S_{1_{A_2}} = 6$	$\sum S_1 = 29$
Subject 2	$S_{2_{A_1}} = 21$	$S_{2_{A_2}} = 10$	$\sum S_2 = 31$
Subject 3	$S_{3_{A_1}} = 19$	$S_{3_{A_2}} = 8$	$\sum S_3 = 27$
Sums for levels of Factor A	$\sum X_{A_1} = 63$	$\sum X_{A_2} = 24$	$\sum X_T = 87$

Table 27.12 Scores of Subjects on Levels of Factor B for Example 27.5

	B_1	B_2	B_3	Subject sums ($\sum S_i$)
Subject 1	$S_{1_{B_1}} = 13$	$S_{1_{B_2}} = 11$	$S_{1_{B_3}} = 5$	$\sum S_1 = 29$
Subject 2	$S_{2_{B_1}} = 13$	$S_{2_{B_2}} = 13$	$S_{2_{B_3}} = 5$	$\sum S_2 = 31$
Subject 3	$S_{3_{B_1}} = 13$	$S_{3_{B_2}} = 9$	$S_{3_{B_3}} = 5$	$\sum S_3 = 27$
Sums for levels of Factor B	$\sum X_{B_1} = 39$	$\sum X_{B_2} = 33$	$\sum X_{B_3} = 15$	$\sum X_T = 87$

As is the case for the **between-subjects factorial analysis of variance** and the **factorial analysis of variance for a mixed design**, the following three F ratios are computed for the **within-subjects factorial analysis of variance**: F_A , F_B , F_{AB} . The equations required for computing the F ratios are summarized in Table 27.13. Table 27.14 summarizes the computations for the **within-subjects factorial analysis of variance** when it is employed to evaluate Example 27.5. In order to compute the F ratios for the **within-subjects factorial analysis of variance**, it is required that the following summary values (which are also computed for the **between-subjects factorial analysis of variance** and the **factorial analysis of variance for a mixed design**) be computed: $[XS]$, $[T]$, $[A]$, $[B]$, and $[AB]$. Since the summary values computed in Tables 27.10–27.12 are identical to those computed in Tables 27.1 and 27.7 (for Example 27.1 and Example 27.4), the same summary values are employed in Tables 27.13 and 27.14 to compute the values $[XS]$, $[T]$, $[A]$, $[B]$, and $[AB]$ (which are, respectively, computed with Equations

27.4–27.8). Thus: $[XS] = 585$, $[T] = 420.5$, $[A] = 505$, $[B] = 472.5$, and $[AB] = 573$. Since the same set of data and the same equations are employed for the **within-subjects factorial analysis of variance**, the **between-subjects factorial analysis of variance**, and the **factorial analysis of variance for a mixed design**, all three analysis of variance procedures yield identical values for $[XS]$, $[T]$, $[A]$, $[B]$, and $[AB]$. Inspection of [Table 27.13](#) also reveals that the **within-subjects factorial analysis of variance**, the **between-subjects factorial analysis of variance**, and the **factorial analysis of variance for a mixed design** employ the same equations to compute the values SS_A , SS_B , SS_{AB} , SS_T , MS_A , MS_B , and MS_{AB} .

In order to compute a number of additional sum of squares values for the **within-subjects factorial analysis of variance**, it is necessary to compute the following three elements which are not computed for the **between-subjects factorial analysis of variance**: $[S]$, $[AS]$, and $[BS]$.

$[S]$, which is computed with Equation 27.70, is employed in [Tables 27.13](#) and [27.14](#) to compute the following values: $SS_{\text{Between-subjects}}$, $SS_{\text{Within-subjects}}$, $SS_{A \times \text{subjects}}$, $SS_{B \times \text{subjects}}$, $SS_{AB \times \text{subjects}}$.

$$[S] = \sum_{i=1}^n \left[\frac{(\sum S_i)^2}{pq} \right] \quad (\text{Equation 27.70})$$

The notation $\sum_{i=1}^n [(\sum S_i)^2/pq]$ in Equation 27.70 indicates that for each of the $n = 3$ subjects, the sum of that subject's three scores (i.e., $\sum S_i$) is squared and divided by pq . The resulting values obtained for the $n = 3$ subjects are summed, yielding the value $[S]$. Employing Equation 27.70, the value $[S] = 421.83$ is computed.

$$[S] = \frac{(29)^2}{6} + \frac{(31)^2}{6} + \frac{(27)^2}{6} = 421.83$$

$[AS]$, which is computed with Equation 27.71, is employed in [Tables 27.13](#) and [27.14](#) to compute the following values: $SS_{A \times \text{subjects}}$, $SS_{AB \times \text{subjects}}$.

$$[AS] = \sum_{i=1}^n \sum_{j=1}^p \left[\frac{(\sum S_{iA_j})^2}{q} \right] \quad (\text{Equation 27.71})$$

The notation $\sum_{i=1}^n \sum_{j=1}^p [(\sum S_{iA_j})^2/q]$ in Equation 27.71 indicates that each of the $p = 2$ S_{iA_j} scores of the $n = 3$ subjects is squared and divided by $q = 3$. The resulting $np = 6$ values are summed, yielding the value $[AS]$. Employing Equation 27.71, the value $[AS] = 510.33$ is computed (which is the same value computed for $[AS]$ when the same set of data are evaluated with the **factorial analysis of variance for a mixed design**).

$$[AS] = \frac{(23)^2}{3} + \frac{(6)^2}{3} + \frac{(21)^2}{3} + \frac{(10)^2}{3} + \frac{(19)^2}{3} + \frac{(8)^2}{3} = 510.33$$

$[BS]$, which is computed with Equation 27.72, is employed in [Tables 27.13](#) and [27.14](#) to compute the following values: $SS_{B \times \text{subjects}}$, $SS_{AB \times \text{subjects}}$.

$$[BS] = \sum_{i=1}^n \sum_{k=1}^q \left[\frac{(\sum S_{iB_k})^2}{p} \right] \quad (\text{Equation 27.72})$$

The notation $\sum_{i=1}^n \sum_{k=1}^q [(\sum S_{i_{B_k}})^2 / p]$ in Equation 27.72 indicates that each of the $q = 3$ $S_{i_{B_k}}$ scores of the $n = 3$ subjects is squared and divided by $p = 2$. The resulting $nq = 9$ values are summed, yielding the value $[BS]$. Employing Equation 27.72, the value $[BS]$ 476.5 is computed.

$$[BS] = \frac{(13)^2}{2} + \frac{(11)^2}{2} + \frac{(5)^2}{2} + \frac{(13)^2}{2} + \frac{(13)^2}{2} + \frac{(5)^2}{2} + \frac{(13)^2}{2} + \frac{(9)^2}{2} + \frac{(5)^2}{2} = 476.5$$

The reader should take note of the following relationships in [Tables 27.13](#) and [27.14](#):

$$SS_{\text{Within-subjects}} = SS_A + SS_B + SS_{AB} + SS_{A \times \text{subjects}} + SS_{B \times \text{subjects}} + SS_{AB \times \text{subjects}}$$

$$SS_T = SS_{\text{Between-subjects}} + SS_{\text{Within-subjects}}$$

$$df_{\text{Within-subjects}} = df_A + df_B + df_{AB} + df_{A \times \text{subjects}} + df_{B \times \text{subjects}} + df_{AB \times \text{subjects}}$$

$$df_T = df_{\text{Between-subjects}} + df_{\text{Within-subjects}}$$

Inspection of [Table 27.2](#), [Tables 27.13/27.14](#), and [Tables 27.8/27.9](#) reveals that if a **between-subjects factorial analysis of variance**, a **within-subjects factorial analysis of variance**, and a **factorial analysis of variance for a mixed design** are employed with the same set of data, identical values are computed for the following: SS_A , SS_B , SS_{AB} , SS_T , df_A , df_B , df_{AB} , df_T , MS_A , MS_B , and MS_{AB} .

In [Table 27.14](#), the error term $MS_{A \times \text{subjects}} = 2$, employed in computing the value $F_A = 42.25$, is analogous to the error term that would be obtained if in evaluating the data for Example 27.5, Factor B was not taken into account, and the data on Factor A were evaluated with a **single-factor within-subjects analysis of variance**. The error term $MS_{B \times \text{subjects}} = .67$, employed in computing the value $F_B = 38.81$, is analogous to the error term that would be obtained if, in evaluating the data for Example 27.5, Factor A was not taken into account, and the data on Factor B were evaluated with a **single-factor within-subjects analysis of variance**. The value $MS_{AB \times \text{subjects}} = 1$, employed in computing the value $F_{AB} = 8$, is a measure of error variability specific to the AB interaction for the **within-subjects factorial analysis of variance**. For a thorough discussion of the derivation of the error terms for the **within-subjects factorial analysis of variance**, the reader should consult books which discuss analysis of variance procedures in greater detail (e.g., Keppel (1991) and Winer *et al.* (1991)).

The following tabled critical values derived from [Table A10](#) are employed in evaluating the three F ratios computed for Example 27.5: a) **Factor A**: For $df_{\text{num}} = df_A = 1$ and $df_{\text{den}} = df_{A \times \text{subjects}} = 2$, $F_{.05} = 18.51$ and $F_{.01} = 98.50$; b) **Factor B**: For $df_{\text{num}} = df_B = 2$ and $df_{\text{den}} = df_{B \times \text{subjects}} = 4$, $F_{.05} = 6.94$ and $F_{.01} = 18.00$; and c) **AB interaction**: For $df_{\text{num}} = df_{AB} = 2$ and $df_{\text{den}} = df_{AB \times \text{subjects}} = 4$, $F_{.05} = 6.94$ and $F_{.01} = 18.00$.

The identical null and alternative hypotheses that are evaluated in Section III of the **between-subjects factorial analysis of variance** are evaluated in the **within-subjects factorial analysis of variance**. In order to reject the null hypothesis in reference to a computed F ratio, the obtained F value must be equal to or greater than the tabled critical value at the prespecified level of significance. Since the computed value $F_A = 42.25$ is greater than $F_{.05} = 18.51$, the alternative hypothesis for Factor A is supported, but only at the .05 level. Since the computed value $F_B = 38.81$ is greater than $F_{.05} = 6.94$ and $F_{.01} = 18.00$, the alternative hypothesis for Factor B is supported at both the .05 and .01 levels. Since the computed value $F_{AB} = 8$ is greater than $F_{.05} = 6.94$, the alternative hypothesis for an interaction between Factors A and B is supported, but only at the .05 level.²⁸

Table 27.13 Summary Table of Equations for the Within-Subjects Factorial Design

Source of variation	SS	df	MS	F
Between-subjects	$[S] - [T]$	$n - 1$		
Within-subjects	$[XS] - [S]$	$n(pq - 1)$		
<i>A</i>	$[A] - [T]$	$p - 1$	$\frac{SS_A}{df_A}$	$F_A = \frac{MS_A}{MS_{A \times \text{subjects}}}$
<i>B</i>	$[B] - [T]$	$q - 1$	$\frac{SS_B}{df_B}$	$F_B = \frac{MS_B}{MS_{B \times \text{subjects}}}$
<i>AB</i>	$[AB] - [A] - [B] + [T]$	$(p - 1)(q - 1)$	$\frac{SS_{AB}}{df_{AB}}$	$F_{AB} = \frac{MS_{AB}}{MS_{AB \times \text{subjects}}}$
<i>A</i> × subjects	$[AS] - [A] - [S] + [T]$	$(p - 1)(n - 1)$	$\frac{SS_{A \times \text{subjects}}}{df_{A \times \text{subjects}}}$	
<i>B</i> × subjects	$[BS] - [B] - [S] + [T]$	$(q - 1)(n - 1)$	$\frac{SS_{B \times \text{subjects}}}{df_{B \times \text{subjects}}}$	
<i>AB</i> × subjects	$[XS] - [AB] - [AS] - [BS] + [A] + [B] + [S] - [T]$	$(p - 1)(q - 1)(n - 1)$	$\frac{SS_{AB \times \text{subjects}}}{df_{AB \times \text{subjects}}}$	
Total	$[XS] - [T]$	$N - 1 = npq - 1$		

Table 27.14 Summary Table of Computations for Example 27.5

Source of variation	SS	df	MS	F
Between-subjects	421.83 - 420.5 = 1.33	3 - 1 = 2		
Within-subjects	585 - 421.83 = 163.17	3[(2)(3) - 1] = 15		
<i>A</i>	505 - 420.5 = 84.5	2 - 1 = 1	$MS_A = \frac{84.5}{1} = 84.5$	$F_A = \frac{84.5}{2} = 42.25$
<i>B</i>	472.5 - 420.5 = 52	3 - 1 = 2	$MS_B = \frac{52}{2} = 26$	$F_B = \frac{26}{.67} = 38.81$
<i>AB</i>	573 - 505 - 472.5 + 420.5 = 16	(2 - 1)(3 - 1) = 2	$MS_{AB} = \frac{16}{2} = 8$	$F_{AB} = \frac{8}{1} = 8$
<i>A</i> × subjects	510.33 - 505 - 421.83 + 420.5 = 4	(2 - 1)(3 - 1) = 2	$MS_{A \times \text{subjects}} = \frac{4}{2} = 2$	
<i>B</i> × subjects	476.5 - 472.5 - 421.83 + 420.5 = 2.67	(3 - 1)(3 - 1) = 4	$MS_{B \times \text{subjects}} = \frac{2.67}{4} = .67$	
<i>AB</i> × subjects	585 - 573 - 510.33 - 476.5 + 505 + 472.5 + 421.83 - 420.5 = 4	(2 - 1)(3 - 1)(3 - 1) = 4	$MS_{AB \times \text{subjects}} = \frac{4}{4} = 1$	
Total	585 - 420.5 = 164.5	18 - 1 = (3)(2)(3) - 1 = 17		

The analysis of the data for Example 27.5 allows the researcher to conclude that both humidity (Factor A) and temperature (Factor B) have a significant impact on problem-solving scores. However, as is the case when the same set of data is evaluated with a **between-subjects factorial analysis of variance**, the relationships depicted by the main effects must be qualified because of the presence of a significant interaction. Although the comparison procedures following the computation of the omnibus F ratios (as well as the other analytical procedures for determining power, effect size, etc.) described in Section VI of the **between-subjects factorial analysis of variance** can be extended to the **within-subjects factorial analysis of variance**, they will not be described in this book. For a full description of such procedures, the reader should consult texts that discuss analysis of variance procedures in greater detail (e.g., Keppel (1991) and Winer *et al.* (1991)).

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Endnotes

1. A **main effect** refers to the effect of one independent variable on the dependent variable, while ignoring the effect any of the other independent variables have on the dependent variable.
2. Although it is possible to conduct a directional analysis, such an analysis will not be described with respect to a factorial analysis of variance. A discussion of a directional analysis when an independent variable is comprised of two levels can be found under the **t test for two independent samples**. In addition, a discussion of one-tailed F values can

be found in Section VI of the latter test under the discussion of the **Hartley's F_{\max} test for homogeneity of variance/ F test for two population variances**. A discussion of the evaluation of a directional alternative hypothesis when there are two or more groups can be found in Section VII of the **chi-square goodness-of-fit test (Test 8)**. Although the latter discussion is in reference to analysis of a k independent samples design involving categorical data, the general principles regarding the analysis of a directional alternative hypothesis are applicable to the analysis of variance.

3. The notational system employed for the factorial analysis of variance procedures described in this chapter is based on Keppel (1991).
4. The value $SS_{WG} = 12$ can also be computed employing the following equation:

$$\begin{aligned}
 SS_{WG} &= \sum_{k=1}^q \sum_{j=1}^p \left[\Sigma X_{AB_{jk}}^2 - \frac{(\Sigma X_{AB_{jk}})^2}{n_{AB_{jk}}} \right] \\
 &= \left[302 - \frac{(30)^2}{3} \right] + \left[29 - \frac{(9)^2}{3} \right] + \left[149 - \frac{(21)^2}{3} \right] + \left[50 - \frac{(12)^2}{3} \right] + \left[50 - \frac{(12)^2}{3} \right] + \left[5 - \frac{(3)^2}{3} \right] \\
 &= 2 + 2 + 2 + 2 + 2 + 2 = 12
 \end{aligned}$$

Note that in the above equation a within-groups sum of squares is computed for each of the $pq = 6$ groups, and $SS_{WG} = 12$ represents the sum of the six sum of squares values.

5. This averaging protocol only applies when there is an equal number of subjects in the groups represented in the specific row or column for which an average is computed.
6. If the factor represented on the abscissa is comprised of two levels (as is the case in [Figure 27.1a](#)), when no interaction is present the lines representing the different levels of the second factor will be parallel to one another by virtue of being equidistant from one another. When the abscissa factor is comprised of more than two factors, the lines can be equidistant but not parallel when no interaction is present.
7. As noted earlier, the fact that the lines are parallel to one another is not a requirement if no interaction is present when the abscissa factor is comprised of three or more levels.
8. If no interaction is present, such comparisons should yield results that are consistent with those obtained when the means of the levels of that factor are contrasted.
9. As noted in Section VI of the **single-factor between-subjects analysis of variance**, a **linear contrast** is equivalent to **multiple t tests/Fisher's LSD test**.
10. Many researchers would elect to employ a comparison procedure that is less conservative than the **Scheffé test**, and thus would not require as large a value as CD_s in order to reject the null hypothesis.
11. The number of pairwise comparisons is $[k(k-1)]/2 = [6(6-1)]/2 = 15$, where $k = pq = (2)(3) = 6$ represents the number of groups.

12. If **Tukey's HSD test** is employed to contrast pairs or sets of marginal means for Factors A and B, the values $q_{(A, df_{WG})}$ and $q_{(B, df_{WG})}$ are, respectively, employed from [Table A13](#). The sample sizes used in Equation 27.45 for Factors A and B are, respectively, nq and np .
13. When there are only two levels involved in analyzing the simple effects of a factor (as is the case with Factor A), the procedure to be described in this section will yield an F value for a simple effect that is equivalent to the F_{comp} value that can be computed by comparing the two groups employing the **linear contrast** procedure described earlier (i.e., the procedure in which Equation 27.40 is employed to compute SS_{comp}).
14. The equation for computing the sum of squares for each of the simple effects of Factor A is noted below.

$$SS_{A \text{ at } B_k} = \sum \left[\frac{(\sum X_{AB_k})^2}{n} \right] - \frac{(\sum \sum X_{AB_k})^2}{np}$$

If $\sum X_{AB_k}$ represents the sum of the scores on Level k of Factor B of subjects who serve under a specific level of Factor A, the notation $\sum[(\sum X_{AB_k})^2/n]$ in the above equation indicates that the sum of the scores for each level of Factor A at a given level of Factor B is squared, divided by n , and the p squared sums are summed. The notation $(\sum \sum X_{AB_k})^2$ represents the square of the sum of scores of the np subjects who serve under the specified level of Factor B.

15. In the case of the simple effects of Factor A, the modified degrees of freedom value is $df_{WG} = p(n - 1)$.
16. The fact that in the example under discussion the tabled critical values employed for evaluating F_{max} are extremely large is due to the small value of n . However, under the discussion of homogeneity of variance under the **single-factor between-subjects analysis of variance**, it is noted that Keppel (1991) suggests employing a more conservative test anytime the value of $F_{\text{max}} \geq 3$.
17. The fact that MS_{WG} is an unbiased estimate of σ_{WG}^2 can be confirmed by the fact that in the discussion of the homogeneity of variance assumption in the previous section, it is noted that the estimated population variance of each group is $\hat{s}_{AB_{jk}}^2 = 1$. The latter value is equivalent to the value $MS_{WG} = 1$ computed for the factorial analysis of variance.
18. The procedure described in this section assumes there is an equal number of subjects in each group. If the latter is true, it is also the case for Example 27.1 that $\mu_G = (\mu_{A_1} + \mu_{A_2})/2$ and $\mu_G = (\mu_{AB_{11}} + \mu_{AB_{12}} + \mu_{AB_{13}} + \mu_{AB_{21}} + \mu_{AB_{22}} + \mu_{AB_{23}})/6$.
19. Different but equivalent forms of Equations 27.51–27.53 were employed to compute **standard omega squared** in the first edition of this book.
20. For a clarification of the use of multiple summation signs, the reader should review Endnote 63 under the **single-factor between-subjects analysis of variance** and Endnote 19 under the **single-factor within-subjects analysis of variance**.

21. The notation X_{ijk} is a simpler form of the notation $X_{i_{AB_{jk}}}$, which is more consistent with the notational format used throughout the discussion of the **between-subjects factorial analysis of variance**.
22. The notation $\sum_{k=1}^q \sum_{j=1}^p \sum_{i=1}^n X_{ijk}$ is an alternative way of writing $\sum X_T$. $\sum_{k=1}^q \sum_{j=1}^p \sum_{i=1}^n X_{ijk}$ indicates that the scores of each of the $n = n_{AB_{jk}}$ subjects in each of the pq groups are summed.
23. Since the interaction sum of squares is comprised of whatever remains of between-groups variability after the contributions of the main effects for Factor A and Factor B have been removed, Equation 27.67 can be derived from the equation noted below which subtracts Equations 27.65 and 27.66 from Equation 27.64.

$$SS_{AB} = n \sum_{k=1}^q \sum_{j=1}^p (\bar{X}_{AB_{jk}} - \bar{X}_T)^2 - nq \sum_{j=1}^p (\bar{X}_{A_j} - \bar{X}_T)^2 - np \sum_{k=1}^q (\bar{X}_{B_k} - \bar{X}_T)^2$$

24. The computation of the harmonic mean is described in Section VI of the **t test for two independent samples**.
25. Some sources note that the subjects employed in such an experiment (or for that matter any experiment involving independent samples) are nested within the level of the factor to which they are assigned, since each subject serves under only one level of that factor.
26. The computational procedure for the **factorial analysis of variance for a mixed design** assumes that there is an equal number of subjects in each of the levels of the between-subjects factor. When the latter is not true, adjusted equations should be employed which can be found in books that describe the **factorial analysis of variance for a mixed design** in greater detail.
27. There are 12 possible presentation orders involving combinations of the two factors ($p!q! = 3!2! = 12$). The sequences for presentation of the levels of both factors are determined in the following manner: If A_1 is followed by A_2 , presentation of the levels of Factor B can be in the six following sequences: 123, 132, 213, 231, 312, 321. If A_2 is followed by A_1 , presentation of the levels of Factor B can be in the same six sequences noted previously. Thus, there are a total of 12 possible sequence combinations. Since there are only six subjects in Example 27.5, only six of the 12 possible sequence combinations can be employed.
28. If Factors A and B are both within-subjects factors and a significant effect is present for the main effects and the interaction, the **within-subjects factorial analysis of variance** would be the most likely of the three factorial analysis of variance procedures discussed to yield significant F ratios. The F_A , F_B , and F_{AB} values obtained in Examples 27.1 and 27.4 are significant at both the .05 and .01 levels when the data are, respectively, evaluated with a **between-subjects factorial analysis of variance** and a **factorial analysis of variance for a mixed design**. However, when Example 27.5 is evaluated with the **within-subjects factorial analysis of variance**, although F_B is significant at both the .05 and .01 levels, F_A and F_{AB} are only significant at the .05 level. This latter result can

be attributed to the fact that the data set employed for the three examples is hypothetical, and is not based on the scores of actual subjects who were evaluated within the framework of a within-subjects factorial design. In point of fact, in the case of the **within-subjects factorial analysis of variance**, the lower value for df_{den} employed for a specific effect (in contrast to the values of df_{den} employed for the **between-subjects factorial analysis of variance** and the **factorial analysis of variance for a mixed design**) will be associated with a tabled critical F value that is larger than the values employed for the latter two tests. Thus, unless there is an actual correlation between subjects' scores under different conditions (which should be the case if a variable is measured within-subjects), the loss of degrees of freedom will nullify the increase in power associated with the **within-subjects factorial analysis of variance** (assuming the data are derived from the appropriate design). The superior power of the **within-subjects factorial analysis of variance** derives from the smaller MS error terms employed in evaluating the main effects and interaction.

Measures of Association/Correlation

Test 28: The Pearson Product-Moment Correlation Coefficient

Test 29: Spearman's Rank-Order Correlation Coefficient

Test 30: Kendall's Tau

Test 31: Kendall's Coefficient of Concordance

Test 32: Goodman and Kruskal's Gamma

Test 28

The Pearson Product-Moment Correlation Coefficient (Parametric Measure of Association/Correlation Employed with Interval/Ratio Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

The **Pearson product-moment correlation coefficient** is one of a number of measures of correlation or association discussed in this book. Measures of correlation are not inferential statistical tests, but are, instead, descriptive statistical measures that represent the degree of relationship between two or more variables. Upon computing a measure of correlation, it is common practice to employ one or more inferential statistical tests in order to evaluate one or more hypotheses concerning the correlation coefficient. The hypothesis stated below is the most commonly evaluated hypothesis for the **Pearson product-moment correlation coefficient**.

Hypothesis evaluated with test In the underlying population represented by a sample, is the correlation between subjects' scores on two variables some value other than zero? The latter hypothesis can also be stated in the following form: In the underlying population represented by the sample, is there a significant linear relationship between the two variables?

Relevant background information on test Developed by Pearson (1896, 1900), the **Pearson product-moment correlation coefficient** is employed with interval/ratio data to determine the degree to which two variables covary (i.e., vary in relationship to one another). Any measure of correlation/association that assesses the degree of relationship between two variables is referred to as a **bivariate** measure of association. In evaluating the extent to which two variables covary, the **Pearson product-moment correlation coefficient** determines the degree to which a linear relationship exists between the variables. One variable (usually designated as the *X* variable) is referred to as the **predictor variable**, since if indeed a linear relationship does exist between the two variables, a subject's score on the predictor variable can be used to predict the subject's score on the second variable. The latter variable, which is referred to as the **criterion variable**, is usually designated as the *Y* variable.¹ The degree of accuracy with which a researcher will be able to predict a subject's score on the criterion variable from the subject's score on the predictor variable will depend upon the strength of the linear relationship between the two variables. The use of correlational data for predictive purposes is summarized under the general subject of **regression analysis** (or more formally, **linear regression analysis**, since, when prediction is discussed in reference to the **Pearson product-moment correlation coefficient**, it is based on the degree of linear relationship between the two variables). A full discussion of regression analysis can be found in Section VI.

The statistic computed for the **Pearson product-moment correlation coefficient** is represented by the letter *r*. *r* is an estimate of ρ (the Greek letter **rho**), which is the correlation between the two variables in the underlying population. *r* can assume any value within the range

of -1 to $+1$ (i.e., $-1 \leq r \leq +1$). Thus, the value of r can never be less than -1 (i.e., r cannot equal -1.2 , -50 , etc.) or be greater than $+1$ (i.e., r cannot equal 1.2 , 50 , etc.). The **absolute value** of r (i.e., $|r|$) indicates the **strength** of the relationship between the two variables. As the absolute value of r approaches 1 , the degree of linear relationship between the variables becomes stronger, achieving the maximum when $|r| = 1$ (i.e., when r equals either $+1$ or -1). The closer the absolute value of r is to 1 , the more accurately a researcher will be able to predict a subject's score on one variable from the subject's score on the other variable. The closer the absolute value of r is to 0 , the weaker the linear relationship between the two variables. As the absolute value of r approaches 0 , the degree of accuracy with which a researcher can predict a subject's score on one variable from the other variable decreases, until finally, when $r = 0$ there is no predictive relationship between the two variables. To state it another way, when $r = 0$ the use of the correlation coefficient to predict a subject's X score from the subject's Y score (or vice versa) will not be any more accurate than a prediction that is based on some random process (i.e., a prediction that is based purely on chance).

The **sign** of r indicates the nature or **direction** of the linear relationship that exists between the two variables. A positive sign indicates a **direct** linear relationship, whereas a negative sign indicates an **indirect** (or **inverse**) linear relationship. A direct linear relationship is one in which a change on one variable is associated with a change on the other variable in the same direction (i.e., an increase on one variable is associated with an increase on the other variable, and a decrease on one variable is associated with a decrease on the other variable). When there is a direct relationship, subjects who have a high score on one variable will have a high score on the other variable, and subjects who have a low score on one variable will have a low score on the other variable. The closer a positive value of r is to $+1$, the stronger the direct relationship between the two variables; whereas the closer a positive value of r is to 0 , the weaker the direct relationship between the variables. Thus, when r is close to $+1$, most subjects who have a high score on one variable will have a comparably high score on the second variable, and most subjects who have a low score on one variable will have a comparably low score on the second variable. As the value of r approaches 0 , the consistency of the general pattern described by a positive correlation deteriorates, until finally, when $r = 0$ there will be no consistent pattern that allows one to predict at above chance a subject's score on one variable if one knows the subject's score on the other variable.

An indirect/inverse relationship is one in which a change on one variable is associated with a change on the other variable in the opposite direction (i.e., an increase on one variable is associated with a decrease on the other variable, and a decrease on one variable is associated with an increase on the other variable). When there is an indirect linear relationship, subjects who have a high score on one variable will have a low score on the other variable, and vice versa. The closer a negative value of r is to -1 , the stronger the indirect relationship between the two variables, whereas the closer a negative value of r is to 0 , the weaker the indirect relationship between the variables. Thus, when r is close to -1 , most subjects who have a high score on one variable will have a comparably low score on the second variable (i.e., as extreme a score in the opposite direction), and most subjects who have a low score on one variable will have a comparably high score on the second variable. As the value of r approaches 0 , the consistency of the general pattern described by a negative correlation deteriorates, until finally, when $r = 0$ there will be no consistent pattern that allows one to predict at above chance a subject's score on one variable if one knows the subject's score on the other variable.

The use of the **Pearson product-moment correlation coefficient** assumes that a linear function best describes the relationship between the two variables. If, however, the relationship between the variables is better described by a curvilinear function, the value of r computed for a set of data may not indicate the actual extent of the relationship between the variables. In view

of this, when a computed r value is equal to or close to 0, a researcher should always rule out the possibility that the two variables are related curvilinearly. One quick way of assessing the likelihood of the latter is to construct a **scatterplot** of the data. A scatterplot, which is described in Section VI, displays the data for a correlational analysis in a graphical format.

It is important to note that correlation does not imply causation. Consequently, if there is a strong correlation between two variables (i.e., the absolute value of r is close to 1), a researcher is not justified in concluding that one variable causes the other variable. Although it is possible that when a strong correlation exists one variable may, in fact, cause the other variable, the information employed in computing the **Pearson product-moment correlation coefficient** does not allow a researcher to draw such a conclusion. This is the case, since extraneous variables that have not been taken into account by the researcher can be responsible for the observed correlation between the two variables.

The **Pearson product-moment correlation coefficient** is based on the following assumptions: a) The sample of n subjects for which the value r is computed is randomly selected from the population it represents; b) The level of measurement upon which each of the variables is based is interval or ratio. Although this assumption is applicable to the conventional use of the **Pearson product-moment correlation coefficient**, there are special cases in which the equation for **Pearson r** can be employed with rank-order data (see Section VI of **Spearman's rank-order correlation coefficient (Test 29)**), and categorical data involving one or both variables (see the discussions of the **phi coefficient (Test 16g)** in Section VII, and the discussion of the **point-biserial correlation coefficient (Test 28h)** in Section IX (the **Addendum**)); c) The two variables have a **bivariate normal distribution**. The assumption of bivariate normality states that each of the variables and the linear combination of the two variables are normally distributed. With respect to the latter, if every possible pair of data points are plotted on a three-dimensional plane, the resulting surface (which will look like a mountain with a rounded peak) will be a three-dimensional normal distribution (i.e., a three-dimensional structure in which any cross-section is a standard normal distribution). Another characteristic of a bivariate normal distribution is that for any given value of the X variable, the scores on the Y variable will be normally distributed, and for any given value of the Y variable, the scores on the X variable will be normally distributed. In conjunction with the latter, the variances for the Y variable will be equal for each of the possible values of the X variable, and the variances for the X variable will be equal for each of the possible values of the Y variable; d) Related to the bivariate normality assumption is the assumption of **homoscedasticity**. Homoscedasticity exists in a set of data if the relationship between the X and Y variables is of equal strength across the whole range of both variables. Tabachnick and Fidell (1989) note that when the assumption of bivariate normality is met, the two variables will be homoscedastic. The concept of homoscedasticity is discussed in Section VII; and e) Another assumption of the **Pearson product-moment correlation coefficient**, referred to as **nonautoregression**, is discussed in many books on business and economics. This latter assumption, which is discussed within the framework of a special case of correlation referred to as **autocorrelation**, is only likely to be violated when pairs of numbers that are derived from a series of n numbers are correlated with one another. A discussion of autocorrelation can be found in Section VII.

II. Example

Example 28.1 *A psychologist conducts a study employing a sample of five children to determine whether there is a statistical relationship between the number of ounces of sugar a ten-year-old child eats per week (which will represent the X variable) and the number of cavities in a child's mouth (which will represent the Y variable). The two scores (ounces of sugar consumed per week*

and number of cavities) obtained for each of the five children follow: **Child 1** (20, 7); **Child 2** (0, 0); **Child 3** (1, 2); **Child 4** (12, 5); **Child 5** (3, 3). Is there a significant correlation between sugar consumption and the number of cavities?

III. Null versus Alternative Hypotheses

Upon computing the **Pearson product-moment correlation coefficient**, it is common practice to determine whether the obtained absolute value of the correlation coefficient is large enough to allow a researcher to conclude that the underlying population correlation coefficient between the two variables is some value other than zero. Section V describes how the latter hypothesis, which is stated below, can be evaluated through use of tables of critical r values or through use of an inferential statistical test that is based on the t distribution.²

Null hypothesis $H_0: \rho = 0$

(In the underlying population the sample represents, the correlation between the scores of subjects on Variable X and Variable Y equals 0.)

Alternative hypothesis $H_1: \rho \neq 0$

(In the underlying population the sample represents, the correlation between the scores of subjects on Variable X and Variable Y equals some value other than 0. This is a **nondirectional alternative hypothesis**, and it is evaluated with a **two-tailed test**. Either a significant positive r value or a significant negative r value will provide support for this alternative hypothesis. In order to be significant, the obtained absolute value of r must be equal to or greater than the tabled critical two-tailed r value at the prespecified level of significance.)

or

$H_1: \rho > 0$

(In the underlying population the sample represents, the correlation between the scores of subjects on Variable X and Variable Y equals some value greater than 0. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. Only a significant positive r value will provide support for this alternative hypothesis. In order to be significant (in addition to the requirement of a positive r value), the obtained absolute value of r must be equal to or greater than the tabled critical one-tailed r value at the prespecified level of significance.)

or

$H_1: \rho < 0$

(In the underlying population the sample represents, the correlation between the scores of subjects on Variable X and Variable Y equals some value less than 0. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. Only a significant negative r value will provide support for this alternative hypothesis. In order to be significant (in addition to the requirement of a negative r value), the obtained absolute value of r must be equal to or greater than the tabled critical one-tailed r value at the prespecified level of significance.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis is rejected.

IV. Test Computations

Table 28.1 summarizes the data for Example 28.1. The following should be noted with respect to Table 28.1: a) The number of subjects is $n = 5$. Each subject has an X score and a Y score, and thus there are five X scores and five Y scores; b) ΣX , ΣX^2 , ΣY , and, ΣY^2 , respectively, represent the sum of the five subjects' scores on the X variable, the sum of the five subjects' squared scores on the X variable, the sum of the five subjects' scores on the Y variable, and the sum of the five subjects' squared scores on the Y variable; and c) An XY score is obtained for each subject by multiplying a subject's X score by the subject's Y score. ΣXY represents the sum of the five subjects' XY scores.

Table 28.1 Summary of Data for Example 28.1

Subject	X	X^2	Y	Y^2	XY
1	20	400	7	49	140
2	0	0	0	0	0
3	1	1	2	4	2
4	12	144	5	25	60
5	3	9	3	9	9
<hr/>					
$\Sigma X = 36$		$\Sigma X^2 = 554$	$\Sigma Y = 17$	$\Sigma Y^2 = 87$	$\Sigma XY = 211$

Although they are not required for computing the value of r , the mean score (\bar{X} and \bar{Y}) and the estimated population standard deviation (\tilde{s}_X and \tilde{s}_Y) for each of the variables are computed (the latter values are computed with Equation I.8). These values are employed in Section VI to derive **regression equations**, which are used to predict a subject's score on one variable from the subject's score on the other variable.

$$\bar{X} = \frac{\Sigma X}{n} = \frac{36}{5} = 7.2 \quad \bar{Y} = \frac{\Sigma Y}{n} = \frac{17}{5} = 3.4$$

$$\tilde{s}_X = \sqrt{\frac{\Sigma X^2 - \frac{(\Sigma X)^2}{n}}{n - 1}} = \sqrt{\frac{554 - \frac{(36)^2}{5}}{5 - 1}} = 8.58$$

$$\tilde{s}_Y = \sqrt{\frac{\Sigma Y^2 - \frac{(\Sigma Y)^2}{n}}{n - 1}} = \sqrt{\frac{87 - \frac{(17)^2}{5}}{5 - 1}} = 2.70$$

Equation 28.1 (which is identical to Equation 17.7, except for the fact that the notations X and Y are used in place of X_1 and X_2) is employed to compute the value of r .³

$$r = \frac{\Sigma XY - \frac{(\Sigma X)(\Sigma Y)}{n}}{\sqrt{\left[\Sigma X^2 - \frac{(\Sigma X)^2}{n} \right] \left[\Sigma Y^2 - \frac{(\Sigma Y)^2}{n} \right]}} \quad (\text{Equation 28.1})$$

Substituting the appropriate values in Equation 28.1, the value $r = .995$ is computed.

$$r = \frac{211 - \frac{(36)(17)}{5}}{\sqrt{\left[554 - \frac{(36)^2}{5}\right]\left[87 - \frac{(17)^2}{5}\right]}} = .995$$

The numerator of Equation 28.1, which is referred to as the **sum of products** (which is summarized with the notation SP_{XY}), will determine the sign of r . If the numerator is a negative value, r will be a negative number. If the numerator is a positive value, r will be a positive number. If the numerator equals zero, r will equal zero. In the case of Example 28.1, $SP_{XY} = \sum XY - [(\sum X)(\sum Y)/n] = 211 - [(36)(17)/5] = 88.6$. The denominator of Equation 28.1 is the square root of the product of the **sum of squares of the X scores** (which is summarized with the notation SS_X), and the **sum of squares of the Y scores** (which is summarized with the notation SS_Y). Thus, $SS_X = \sum X^2 - [(\sum X)^2/n] = 554 - [(36)^2/5] = 294.8$ and $SS_Y = \sum Y^2 - [(\sum Y)^2/n] = 87 - [(17)^2/5] = 29.2$. The aforementioned sum of squares values represent the numerator of the equation for computing the estimated population standard deviation of the X and Y scores (i.e., Equation 1.8). Employing the notation for the sum of products and the sums of squares, the equation for the **Pearson product-moment correlation coefficient** can be expressed as follows: $r = SP_{XY}/\sqrt{SS_X SS_Y}$.

The reader should take note of the fact that each of the sum of squares values must be a positive number. If either of the sum of squares values is a negative number, it indicates that a computational error has been made. The only time a sum of squares value will equal zero, will be if all of the subjects have the identical score on the variable for which the sum of squares is computed. Anytime one or both of the sum of squares values equals zero, Equation 28.1 will be insoluble. It is noted in Section I that the computed value of r must fall within the range $-1 \leq r \leq +1$. Consequently, if the value of r is less than -1 or greater than $+1$, it indicates that a computational error has been made.

V. Interpretation of the Test Results

The obtained value $r = .995$ is evaluated with **Table A16 (Table of Critical Values for Pearson r)** in the **Appendix**. The degrees of freedom employed for evaluating the significance of r are computed with Equation 28.2.

$$df = n - 2 \quad \text{(Equation 28.2)}$$

Employing Equation 28.2, the value $df = 5 - 3 = 2$ is computed. Using **Table A16**, it can be determined that the tabled critical two-tailed r values at the .05 and .01 levels of significance are $r_{.05} = .878$ and $r_{.01} = .959$, and the tabled critical one-tailed r values at the .05 and .01 levels of significance are $r_{.05} = .805$ and $r_{.01} = .934$.

The following guidelines are employed in evaluating the null hypothesis $H_0: \rho = 0$.

a) If the nondirectional alternative hypothesis $H_1: \rho \neq 0$ is employed, the null hypothesis can be rejected if the obtained absolute value of r is equal to or greater than the tabled critical two-tailed value at the prespecified level of significance.

b) If the directional alternative hypothesis $H_1: \rho > 0$ is employed, the null hypothesis can be rejected if the sign of r is positive, and the value of r is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

c) If the directional alternative hypothesis $H_1: \rho < 0$ is employed, the null hypothesis can be rejected if the sign of r is negative, and the absolute value of r is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

Employing the above guidelines, the nondirectional alternative hypothesis $H_1: \rho \neq 0$ is supported at the .05 level, since the computed value $r = .955$ is greater than the tabled critical two-tailed value $r_{.05} = .878$. It is not, however, supported at the .01 level, since $r = .955$ is less than the tabled critical two-tailed value $r_{.01} = .959$.

The directional alternative hypothesis $H_1: \rho > 0$ is supported at both the .05 and .01 levels, since the computed value $r = .955$ is a positive number that is greater than the tabled critical one-tailed values $r_{.05} = .805$ and $r_{.01} = .934$.

The directional alternative hypothesis $H_1: \rho < 0$ is not supported, since the computed value $r = .955$ is a positive number. In order for the alternative hypothesis $H_1: \rho < 0$ to be supported, the computed value of r must be a negative number (as well as the fact that the absolute value of r must be equal to or greater than the tabled critical one-tailed value at the prespecified level of significance).

It may seem surprising that such a large correlation (i.e., an r value that almost equals 1) is not significant at the .01 level. Inspection of [Table A16](#) reveals that when the sample size is small (as is the case in Example 28.1), the tabled critical r values are relatively large. The large critical values reflect the fact that the smaller the sample size, the higher likelihood of sampling error resulting in a spuriously inflated correlation. At this point it is worth noting that there are a number of factors which can dramatically influence the value of r , and such factors are much more likely to distort the computed value of a correlation coefficient when the sample size is small. The following are among those factors that can dramatically influence the value of r : a) If the range of scores on either the X or Y variable is restricted, the absolute value of r will be reduced; b) A correlation based on a sample which is characterized by the presence of extreme scores on one or both of the variables (even though the scores are not extreme enough to be considered **outliers**, which are atypically extreme scores) may be spuriously high (i.e., the absolute value of r will be higher than the absolute value of ρ in the underlying population); and c) The presence of one or more outliers can grossly distort the absolute value of r , or even affect the sign of r (outliers are discussed in detail in Section VII of the ***t* test for two independent samples (Test 11)**).

Further examination of [Table A16](#) reveals that as the value of n increases, the tabled critical values at a given level of significance decrease, until finally when n is quite large the tabled critical values are quite low. What this translates into is that when the sample size is extremely large, an absolute r value that is barely above zero will be statistically significant. Keep in mind, however, that the alternative hypothesis that is evaluated only stipulates that the underlying population correlation is some value other than zero. The distinction between statistical versus practical significance (which is discussed in Section VI of the ***t* test for two independent samples**) is germane to this discussion, in that a small correlation may be statistically significant, yet not be of any practical and/or theoretical value. It should be noted, however, that in many instances a significant correlation which is close to zero may be of practical and/or theoretical significance.

Test 28a: Test of significance for a Pearson product-moment correlation coefficient In the event a researcher does not have access to [Table A16](#), Equation 28.3, which employs the t distribution, provides an alternative way of evaluating the null hypothesis $H_0: \rho = 0$.

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \quad (\text{Equation 28.3})$$

Substituting the appropriate values in Equation 28.3, the value $t = 5.58$ is computed.

$$t = \frac{.955\sqrt{5-2}}{\sqrt{1-(.955)^2}} = 5.58$$

The computed value $t = 5.58$ is evaluated with **Table A2 (Table of Student's t Distribution)** in the **Appendix**. The degrees of freedom employed in evaluating Equation 28.3 are $df = n - 2$. Thus, $df = 5 - 2 = 3$. For $df = 3$, the tabled critical two-tailed .05 and .01 values are $t_{.05} = 3.18$ and $t_{.01} = 5.84$, and the tabled critical one-tailed .05 and .01 values are $t_{.05} = 2.35$ and $t_{.01} = 4.54$. Since the sign of the t value computed with Equation 28.3 will always be the same as the sign of r , the guidelines described earlier in reference to **Table A16** for evaluating an r value can also be applied in evaluating the t value computed with Equation 28.3 (i.e., substitute t in place of r in the text of the guidelines for evaluating r).

Employing the guidelines, the nondirectional alternative hypothesis $H_1: \rho \neq 0$ is supported at the .05 level, since the computed value $t = 5.58$ is greater than the tabled critical two-tailed value $t_{.05} = 3.18$. It is not, however, supported at the .01 level, since $t = 5.58$ is less than the tabled critical two-tailed value $t_{.01} = 5.84$.

The directional alternative hypothesis $H_1: \rho > 0$ is supported at both the .05 and .01 levels, since the computed value $t = 5.58$ is a positive number that is greater than the tabled critical one-tailed values $t_{.05} = 2.35$ and $t_{.01} = 4.54$.

The directional alternative hypothesis $H_1: \rho < 0$ is not supported, since the computed value $t = 5.58$ is a positive number. In order for the alternative hypothesis $H_1: \rho < 0$ to be supported, the computed value of t must be a negative number (as well as the fact that the absolute value of t must be equal to or greater than the tabled critical one-tailed value at the prespecified level of significance).

Note that the results obtained through use of Equation 28.3 are consistent with those that are obtained when **Table A16** is employed.⁴ A summary of the analysis of Example 28.1 follows: It can be concluded that there is a significant positive correlation between the number of ounces of sugar a ten-year-old child eats and the number of cavities in a child's mouth. This result can be summarized as follows (if it is assumed the nondirectional alternative hypothesis $H_1: \rho \neq 0$ is employed): $r = .955, p < .05$.

The coefficient of determination The square of a computed r value (i.e., r^2) is referred to as the **coefficient of determination**. r^2 represents the proportion of variance on one variable that can be accounted for by variance on the other variable.⁵ The use of the term "accounted for" in the previous sentence should not be interpreted as indicating that a cause-effect relationship exists between the two variables. As noted in Section I, a substantial correlation between two variables does not allow one to conclude that one variable causes the other.

For Example 28.1 the coefficient of determination is computed to be $r^2 = (.955)^2 = .912$, which expressed as a percentage is 91.2%.⁶ This indicates that 91.2% of the variation on the X variable can be accounted for on the basis of variability on the Y variable (or vice versa). Although it is possible that X causes Y (or that Y causes X), it is also possible that one or more extraneous variables which are related to X and/or Y , which have not been taken into account in the analysis, are the real reason for the strong relationship between the two variables. In order

to demonstrate that the amount of sugar a child eats is the direct cause of the number of cavities he or she develops, a researcher would be required to conduct an experiment in which the amount of sugar consumed is a manipulated independent variable, and the number of cavities is the dependent variable. As noted in the **Introduction** of the book, an experiment in which the independent variable is directly manipulated by the researcher is often referred to as a **true experiment**. If a researcher conducts a true experiment to evaluate the relationship between the amount of sugar eaten and the number of cavities, such a study would require randomly assigning a representative sample of young children to two or more groups. By virtue of random assignment, it would be assumed that the resulting groups are comparable to one another. Each of the groups would be differentiated from one another on the basis of the amount of sugar the children within a group consume. Since the independent variable is manipulated, the amount of sugar consumed by each group is under the direct control of the experimenter. Any observed differences on the dependent variable between the groups at some later point in time could be attributed to the manipulated independent variable. Thus, if, in fact, significant group differences with respect to the number of cavities are observed, the researcher would have a reasonable basis for concluding that sugar consumption is responsible for such differences.

Whereas the correlational study represented by Example 28.1 is not able to control for potentially confounding variables, the true experiment described above is able control for such variables. Common sense suggests, however, that practical and ethical considerations would make it all but impossible to conduct the sort of experiment described above. Realistically, in a democratic society a researcher cannot force a parent to feed her child a specified amount of sugar if the parent is not naturally inclined to do so. Even if a researcher discovers that through the use of monetary incentives she can persuade some parents to feed their children different amounts of sugar than they deem prudent, the latter sort of inducement would most likely compromise a researcher's ability to randomly assign subjects to groups, not to mention the fact that it would be viewed as unethical by many people. Consequently, if a researcher is inclined to conduct a study evaluating the relationship between sugar consumption and the number of cavities, it is highly unlikely that sugar consumption would be employed as a manipulated independent variable. In order to assess what, if any, relationship there is between the two variables, it is much more likely that a researcher would solicit parents whose children ate large versus moderate versus small amounts of sugar, and use the latter as a basis for defining her groups. In such a study, the amount of sugar consumed would be a nonmanipulated independent variable (since it represents a preexisting subject characteristic). The information derived from this type of study (which is commonly referred to as an **ex post facto study** or a **natural experiment**) is correlational in nature. This is the case, since in any study in which the independent variable is not manipulated by the experimenter, one is not able to effectively control for the influence of potentially confounding variables. Thus, if, in fact, differences are observed between two or more groups in an ex post facto study, although such differences may be due to the independent variable, they can also be due to extraneous variables. Consequently, in the case of the example under discussion, any observed differences in the number of cavities between two or more groups can be due to extraneous factors such as maternal prenatal health care, different home environments, dietary elements other than sugar, socioeconomic and/or educational differences between the families that comprise the different groups, etc.

VI. Additional Analytical Procedures for the Pearson Product-Moment Correlation Coefficient and/or Related Tests

1. Derivation of a regression line The obtained value $r = .955$ suggests a strong direct relationship between sugar consumption (X) and the number of cavities (Y). The high positive

value of the correlation coefficient suggests that as the number of ounces of sugar consumed increases, there is a corresponding increase in the number of cavities. This is confirmed in [Figure 28.1](#) which is a **scatterplot** of the data for Example 28.1. A scatterplot depicts the data employed in a correlational analysis in a graphical format. Each subject's two scores are represented by a single point on the scatterplot. The point that depicts a subject's two scores is arrived at by moving horizontally on the abscissa (X -axis) the number of units that corresponds to the subject's X score, and moving vertically on the ordinate (Y -axis) the number of units that corresponds to the subject's Y score.

Employing the scatterplot, one can visually estimate the straight line that comes closest to passing through all of the data points. This line is referred to as the **regression line** (also known as the **line of best fit**). In actuality, there are two regression lines. The line commonly determined is **the regression line of Y on X** . The latter line is employed to predict a subject's Y score (which represents the criterion variable) by employing the subject's X score (which represents the predictor variable). The second regression line, **the regression line of X on Y** , allows one to predict a subject's X score by employing the subject's Y score. As will be noted later in this discussion, the only time the two regression lines will be identical is when the absolute value of r equals 1. Because X is usually designated as the predictor variable and Y as the criterion variable, the **regression line of Y on X** is the more commonly determined of the two regression lines.

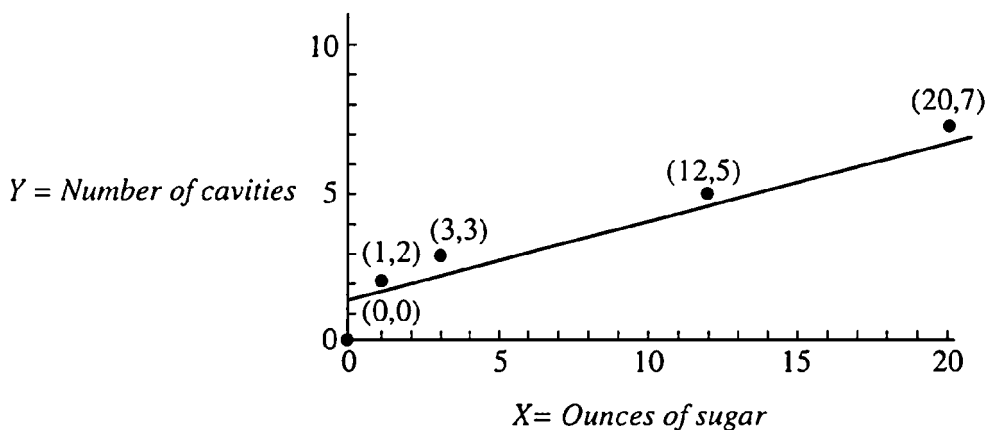


Figure 28.1 Scatterplot for Example 28.1

The **regression line of Y on X** (which, along with the **regression line of X on Y** , is determined mathematically later in this section) has been inserted in [Figure 28.1](#). Note that the line is positively sloped — i.e., the lowest part of the line is on the lower left of the graph with the line slanting upward to the right. A line that is positively sloped reflects the fact that a change on one variable in a specific direction is accompanied by a change in the other variable in the same direction. A positive correlation will always result in a positively sloped regression line. A negative correlation, on the other hand, will always result in a negatively sloped regression line. In a negatively sloped regression line, the upper part of the line is at the left of the graph and the

line slants downward as one moves to the right. A line that is negatively sloped reflects the fact that a change on one variable in a specific direction is accompanied by a change in the other variable in the opposite direction.

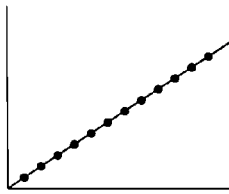
Whereas the slope of the regression line indicates whether a computed r value is a positive or negative number, the magnitude of the absolute value of r reflects how close the n data points fall in relation to the regression line. When $r = +1$ or $r = -1$, all of the data points fall on the regression line. As the absolute value of r deviates from 1 and moves toward 0, the data points deviate further and further from the regression line. Figure 28.2 depicts a variety of hypothetical regression lines, which are presented to illustrate the relationship between the sign and absolute value of r and the regression line.

In Figure 28.2 the regression lines (a), (b), (c), and (d) are positively sloped, and are thus associated with a positive correlation. Lines (e), (f), (g), and (h), on the other hand, are negatively sloped, and are associated with a negative correlation. Note that in each graph, the closer the data points are to the regression line, the closer the absolute value of r is to one. Thus, in graphs (a)–(h), the strength of the correlation (i.e., maximum, strong, moderate, weak) is a function of how close the data points are to the regression line.

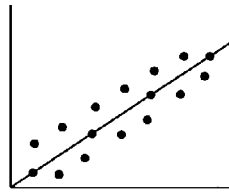
The use of the terms strong, moderate, and weak in relation to specific values of correlation coefficients is somewhat arbitrary. For the purpose of discussion the following rough guidelines will be employed for designating the strength of a correlation coefficient: a) If $|r| \geq .7$, a correlation is considered to be strong; b) If $.3 \leq |r| < .7$, a correlation is considered to be moderate; and c) If $|r| < .3$, a correlation is considered to be weak. In point of fact, most statistically significant correlations in the scientific literature are in the weak to moderate range. As noted earlier, although such correlations are not always of practical and/or theoretical importance, there are many instances where they are.

Graphs (i) and (j) in Figure 28.2 depict data which result in a correlation of zero, since in both instances the distribution of data points is random and, consequently, a straight line cannot be used to describe the relationship between the two variables with any degree of accuracy. Whenever the **Pearson-moment correlation coefficient** equals zero, the regression line will be parallel to either the X -axis (as in Graph (i)) or the Y -axis (as in Graph (j)), depending upon which regression line is drawn.

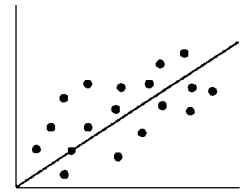
Two other instances in which the regression line is parallel to the X -axis or the Y -axis are depicted in Graphs (k) and (l). Both of these graphs depict data for which a value of r cannot be computed. The data depicted in graphs (k) and (l) illustrate that in order to compute a coefficient of correlation, there must be variability on both the X and the Y variables. Specifically, in Graph (k) the regression line is parallel to the X -axis. The configuration of the data upon which this graph is based indicates that, although there is variability with respect to subjects' scores on the X variable, there is no variability with respect to their scores on the Y variable — i.e., all of the subjects obtain the identical score on the Y variable. As a result of the latter, the computed value for the estimated population variance for the Y variable will equal zero. When, in fact, the value of the variance for the Y variable equals zero, the sum of squares of the Y scores will equal zero (i.e., $SS_Y = \sum Y^2 - [(\sum Y)^2/n] = 0$). The sum of squares of the Y scores (which is the numerator of the equation for computing the estimated population variance of the Y scores) is, as noted earlier, one of the elements that comprises the denominator of Equation 28.1. Consequently, if the sum of squares of the Y scores equals zero, the latter equation becomes insoluble. Note that if the regression line depicted in Graph (k) is employed to predict a subject's Y score from the subject's X score, all subjects are predicted to have the same score. If, in fact, all subjects have the same Y score, there is no need to employ the regression line to make a prediction.



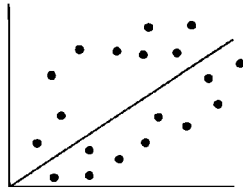
(a) $r = +1$
Maximum positive correlation



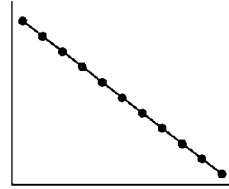
(b) $r = .80$
Strong positive correlation



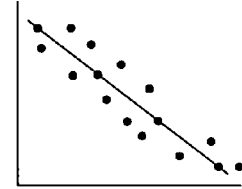
(c) $r = .50$
Moderate positive correlation



(d) $r = .20$
Weak positive correlation



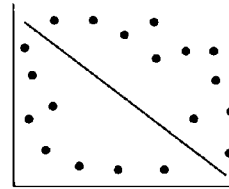
(e) $r = -1$
Maximum negative correlation



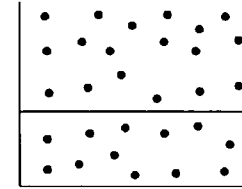
(f) $r = -.80$
Strong negative correlation



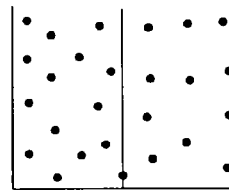
(g) $r = -.50$
Moderate negative correlation



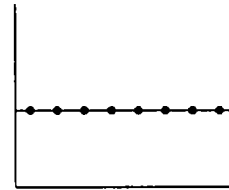
(h) $r = -.20$
Weak negative correlation



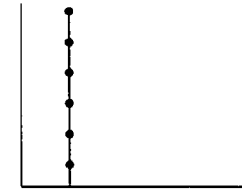
(i) $r = 0$
No correlation



(j) $r = 0$
No correlation



(k) Value of r
cannot be computed



(l) Value of r
cannot be computed



(m) Value of r
cannot be computed

Figure 28.2 Hypothetical Regression Lines

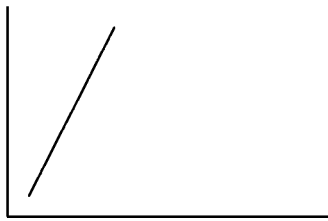
Graph (l) illustrates a regression line that is parallel to the Y -axis. The configuration of the data upon which the latter graph is based indicates that, although there is variability with respect to subjects' scores on the Y variable, there is no variability with respect to their scores on the X variable — i.e., all of the subjects obtain the identical score on the X variable. As a result of the latter, the computed value for the estimated population variance for the X variable will equal zero. When, in fact, the value of the variance for the X variable equals zero, the sum of squares of the X scores will equal zero (i.e., $SS_X = \sum X^2 - [(\sum X)^2/n] = 0$). The sum of squares of the X scores (which is the numerator of the equation for computing the estimated population variance of the X scores) is, as noted earlier, one of the elements that comprises the denominator of Equation 28.1. Consequently, if the sum of squares of the X scores equals zero, the latter equation becomes insoluble. Note that if the regression line depicted in Graph (l) is employed to predict a subject's X score from the subject's Y score, all subjects are predicted to have the same X score. If, in fact, all subjects have the same X score, there is no need to employ the regression line to make a prediction.

If both the X and Y variable have no variability (i.e., all subjects obtain the identical score on the X variable and all subjects obtain the identical score on the Y variable), the resulting graph will consist of a single point (which is the case for Graph (m)). Thus, the single point in Graph (m) indicates that each of the n subjects in a sample obtains identical scores on both the X and Y variables.

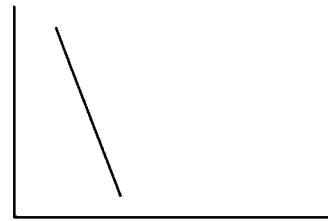
At this point in the discussion, the role of the slope of a regression line will be clarified. The slope of a line indicates the number of units the Y variable will change if the X variable is incremented by one unit. This definition for the slope is applicable to the **regression line of Y on X** . The slope of the **regression line of X on Y** , on the other hand, indicates the number of units the X variable will change if the Y variable is incremented by one unit. The discussion to follow will employ the definition of the slope in reference to the **regression line of Y on X** .

A line with a large positive slope or large negative slope is inclined in an upward direction away from the X -axis — i.e., like a hill with a high grade. The more the magnitude of the positive slope increases, the more the line approaches being parallel to the Y -axis. A line with a small positive slope or small negative slope has a minimal inclination in relation to the X -axis — i.e., like a hill with a low grade. The smaller the slope of a line, the more the line approaches being parallel to the X -axis. The graphs in [Figure 28.3](#) reflect the following degrees of slope: Graphs (a) and (b), respectively, depict lines with a large positive slope and a large negative slope; Graphs (c) and (d), respectively, depict lines with a moderate positive slope and a moderate negative slope (i.e., the severity of the angle in relation to the X -axis is in between that of a line with a large slope and a small slope); Graphs (e) and (f), respectively, depict lines with a small positive slope and a small negative slope.

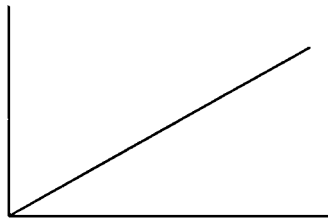
It is important to keep in mind that although the slope of the **regression line of Y on X** plays a role in determining the specific value of Y that is predicted from the value of X , the magnitude of the slope is not related to the magnitude of the absolute value of the coefficient of correlation. A regression line with a large slope can be associated with a correlation coefficient that has a large, moderate, or small absolute value. In the same respect, a regression line with a small slope can be associated with a correlation coefficient that has a large, moderate, or small absolute value. Thus, the accuracy of a prediction is not a function of the slope of the regression line. Instead, it is a function of how far removed the data points are from the regression line. To illustrate this point, let us assume that a regression line which has a large positive slope (such as Graph (a) in [Figure 28.3](#)) is being used to predict Y scores for a set of X scores that are one unit apart from one another. As the magnitude of an X score increases by one unit, there is a sizeable increase in the Y score predicted for each subsequent value of X . In the opposite respect, if the regression line has a small positive slope (such as Graph (e) in [Figure 28.3](#)), as the magnitude of an X score



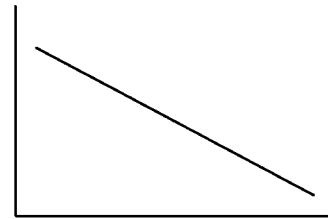
(a) Large positive slope



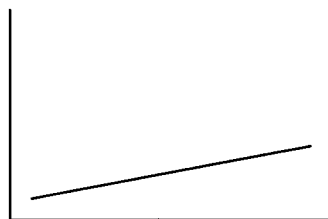
(b) Large negative slope



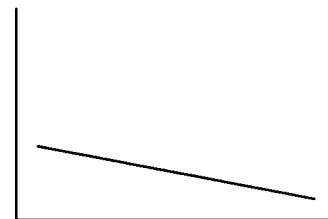
(c) Moderate positive slope



(d) Moderate negative slope



(e) Small positive slope



(f) Small negative slope

Figure 28.3 Hypothetical Regression Lines

increases by one unit, there is a minimal increase in the Y score predicted for each subsequent value of X . It is important to note, however, that in both of the aforementioned examples, regardless of whether the slope of the regression line is large or small, the accuracy of the predicted Y scores will not be affected by the magnitude of the slope of the line. Consequently, for any of the regression lines depicted in Figure 28.3, the n data points can fall on, close to, or be far removed from the regression line.

Mathematical derivation of the regression line The most accurate way to determine the regression line is to compute, through use of a procedure referred to as the **method of least squares**, the equation of the straight line that comes closest to passing through all of the data points. As noted earlier, in actuality there are two regression lines — **the regression line of Y on X** (which is employed to predict a subject's Y score by employing the subject's X score), and **the regression line of X on Y** (which is employed to predict a subject's X score by employing the subject's Y score). The equations for the two regression lines will always be different, except when the absolute value of r equals 1. When $|r| = 1$, the two regression lines are identical (both visually and algebraically). The reason why the two regression lines are always different (except when $|r| = 1$) is because the **regression line of Y on X** is based on the equation that results in the **minimum squared distance** of all the data points from the line, when the distance of the points from the line is measured **vertically** (i.e., \uparrow or \downarrow). On the other hand, the **regression line of X on Y** is based on the minimum squared distance of the data points from the line, when the distance of the points from the line is measured **horizontally** (i.e., \rightarrow or \leftarrow).⁷ Since when $|r| = 1$ all the points fall on the regression line, both the vertical and horizontal squared distance for each data point equals zero. Consequently, when $|r| = 1$ the two regression lines are identical.

The **regression line of Y on X** is determined with Equation 28.4.

$$Y' = a_Y + b_Y X \quad (\text{Equation 28.4})$$

Where: Y' represents the predicted Y score for a subject
 X represents the subject's X score that is used to predict the value Y'
 a_Y represents the Y intercept, which is the point at which the regression line crosses the Y -axis
 b_Y represents the slope of the **regression line of Y on X**

In order to derive Equation 28.4, the values of b_Y and a_Y must be computed. Either Equation 28.5 or Equation 28.6 can be employed to compute the value b_Y . The latter equations are employed below to compute the value $b_Y = .30$.

$$b_Y = \frac{SP_{XY}}{SS_X} = \frac{\Sigma XY - \frac{(\Sigma X)(\Sigma Y)}{n}}{\Sigma X^2 - \frac{(\Sigma X)^2}{n}} = \frac{211 - \frac{(36)(17)}{5}}{554 - \frac{(36)^2}{5}} = .30 \quad (\text{Equation 28.5})$$

$$b_Y = r \left(\frac{\bar{s}_Y}{\bar{s}_X} \right) = (.955) \left(\frac{2.70}{8.58} \right) = .30 \quad (\text{Equation 28.6})$$

Equation 28.7 is employed to compute the value a_Y . The latter equation is employed below to compute the value $a_Y = 1.24$.

$$a_Y = \bar{Y} - b_Y \bar{X} = 3.4 - (.30)(7.2) = 1.24 \quad (\text{Equation 28.7})$$

Substituting the values $a_Y = 1.24$ and $b_Y = .30$ in Equation 28.4, we determine that the equation for **regression line of Y on X** is $Y' = 1.24 + .3X$. Since two points can be used to construct a straight line, we can select two values for X and substitute each value in Equation 28.4, and solve for the values that would be predicted for Y' . Each set of values that is comprised of an X score and the resulting Y' value will represent one point on the regression line. Thus, if we plot any two points derived in this manner and connect them, the resulting line is the **regression line of Y on X**. To demonstrate this, if the value $X = 0$ is substituted in the regression equation, it yields the value $Y' = 1.24$ (which equals the value of a_Y): $Y' = 1.24 - (.30)(0) = 1.24$. Thus, the first point that will be employed in constructing the regression line is (0, 1.24). If we next substitute the value $X = 5$ in the regression equation, it yields the value $Y' = 2.74$: $Y' = 1.24 + (.30)(5) = 2.74$. Thus, the second point to be used in constructing the regression line is (5, 2.74). The regression line that results from connecting the points (0, 1.24) and (5, 2.74) is displayed in [Figure 28.4](#).

If the researcher wants to predict a subject's score on the Y variable by employing the subject's score on the X variable, the predicted value Y' can be derived either from the regression equation or from [Figure 28.4](#). If the regression equation is employed, the value Y' is derived by substituting a subject's X score in the equation (which is the same procedure that is employed to determine the two points that are used to construct the regression line). Thus, if a child consumes ten ounces of sugar per week, employing $X = 10$ in the regression equation, the predicted number of cavities for the child is $Y' = 1.24 + (.30)(10) = 4.24 = 4.24$. In using [Figure 28.4](#) to predict the value of Y' , we identify the point on the X -axis which corresponds to the subject's score on

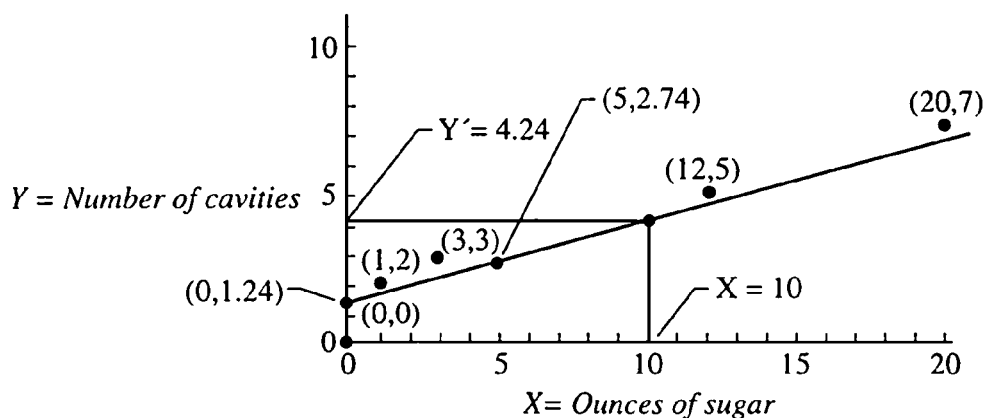


Figure 28.4 Regression Line of Y on X for Example 28.1

the X variable. A perpendicular line is erected from that point until it intersects the regression line. At the point the perpendicular line intersects the regression line, a second perpendicular line is dropped to the Y -axis. The point at which the latter perpendicular line intersects the Y -axis corresponds to the predicted value Y' . This procedure, which is illustrated in Figure 28.4, yields the same value $Y' = 4.24$, which is obtained when the regression equation is employed.

The **regression line of X on Y** is determined with Equation 28.8.

$$X' = a_X + b_X Y \quad (\text{Equation 28.8})$$

Where: X' represents the predicted X score for a subject

Y represents the subject's Y score which is used to predict the value X'

a_X represents the X intercept, which is the point at which the regression line crosses the X -axis

b_X represents the slope of the **regression line of X on Y**

In order to derive Equation 28.8, the values of b_X and a_X must be computed. Either Equation 28.9 or Equation 28.10 can be employed to compute the value b_X . The latter equations are employed below to compute the value $b_X = 3.03$.

$$b_X = \frac{SP_{XY}}{SS_Y} = \frac{\sum XY - \frac{(\sum X)(\sum Y)}{n}}{\sum Y^2 - \frac{(\sum Y)^2}{n}} = \frac{211 - \frac{(36)(17)}{5}}{87 - \frac{(17)^2}{5}} = 3.03 \quad (\text{Equation 28.9})$$

$$b_X = r \left(\frac{\bar{s}_X}{\bar{s}_Y} \right) = (.955) \left(\frac{8.58}{2.70} \right) = 3.03 \quad (\text{Equation 28.10})$$

Equation 28.11 is employed to compute the value a_X . The latter equation is employed below to compute the value $a_X = -3.10$.

$$a_X = \bar{X} - b_X \bar{Y} = 7.2 - (3.03)(3.4) = -3.10 \quad (\text{Equation 28.11})$$

Substituting the values $a_X = -3.10$ and $b_X = 3.03$ in Equation 28.8, we determine that the

equation for **regression line of X on Y** is $X' = -3.10 + 3.03Y$. Since two points can be used to construct a straight line, we can select two values for Y and substitute each value in Equation 28.8, and solve for the values that would be predicted for X' . Each set of values that is comprised of a Y score and the resulting X' value will represent one point on the regression line. Thus, if we plot any two points derived in this manner and connect them, the resulting line is the **regression line of X on Y** . To demonstrate this, if the value $Y = 0$ is substituted in the regression equation, it yields the value $X' = -3.10$ (which equals the value of a_X): $X' = -3.10 + (3.03)(0) = -3.10$. Thus, the first point that will be employed in constructing the regression line is $(-3.10, 0)$. If we next substitute the value $Y = 5$ in the regression equation, it yields the value $X' = 12.05$: $X' = -3.10 + (3.03)(5) = 12.05$. Thus, the second point to be used in constructing the regression line is $(12.05, 5)$. The regression line that results from connecting the points $(-3.10, 0)$ and $(12.05, 5)$ is displayed in Figure 28.5. Note that since the value $Y = 0$ results in a negative X value, the X -axis in Figure 28.5 must be extended to the left of the origin in order to accommodate the value $X = -3.10$.

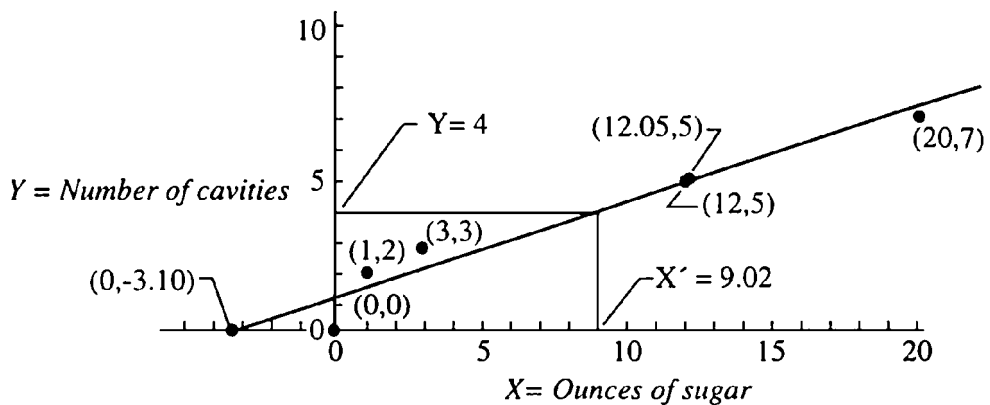


Figure 28.5 Regression Line of X on Y for Example 28.1

If the researcher wants to predict a subject's score on the X variable by employing the subject's score on the Y variable, the predicted value X' can be derived either from the regression equation or from Figure 28.5. If the regression equation is employed, the value X' is derived by substituting a subject's Y score in the equation (which is the same procedure that is employed to determine the two points that are used to construct the regression line). Thus, if a child has four cavities, employing $Y = 4$ in the regression equation, the predicted number of ounces of sugar the child eats per week is $X' = -3.10 + (3.03)(4) = 9.02$. In using Figure 28.5 to predict the value of X' , we identify the point on the Y -axis which corresponds to the subject's score on the Y variable. A perpendicular line is erected from that point until it intersects the regression line. At the point the perpendicular line intersects the regression line, a second perpendicular line is dropped to the X -axis. The point at which the latter perpendicular line intersects the X -axis corresponds to the predicted value X' . This procedure, which is illustrated in Figure 28.5, yields the same value $X' = 9.02$, which is obtained when the regression equation is employed.

The protocol described in this section for deriving a regression equation does not provide any information regarding the accuracy of prediction that will result from such an equation. The **standard error of estimate**, which is discussed in the next section, is used as an index of accuracy in regression analysis. The standard error of estimate is a function of a set of n deviation scores that are referred to as **residuals**. A **residual** is the difference between the predicted value of the criterion variable for a subject (i.e., Y' or X'), and a subject's actual score on the criterion

variable (i.e., Y or X). A discussion of the role of residuals in regression analysis can be found in Section VII.

In closing the discussion of the derivation of a regression line, it is important to emphasize that in some instances where the value of r is equal to or close to zero, there may actually be a curvilinear relationship between the two variables. When the absolute value of r is such that there is a weak to moderate relationship between the variables, if, in fact, a curvilinear function best describes the relationship between the variables, it will provide a more accurate basis for prediction than will the straight line derived through use of the method of least squares. One advantage of constructing a scatterplot is that it allows a researcher to visually assess whether or not a curvilinear function is more appropriate than a straight line in describing the relationship between the variables. If the latter is true, the researcher should derive the equation for the appropriate curve. Although the derivation of equations for curvilinear functions will not be described in this book, it is discussed in many books on correlation and regression.

2. The standard error of estimate The **standard error of estimate** is a standard deviation of the distribution of error scores employed in regression analysis. More specifically, it is an index of the difference between the predicted versus the actual value of the criterion variable. The standard error of estimate for the **regression line of Y on X** (which is represented by the notation $s_{Y.X}$) represents the standard deviation of the values of Y for a specific value of X . The standard error of estimate for the **regression line of X on Y** (which is represented by the notation $s_{X.Y}$) represents the standard deviation of the values of X for a specific value of Y . Thus, in Example 28.1, $s_{Y.X}$ represents the standard deviation for the number of cavities of any subject whose weekly sugar consumption is equal to a specific number of ounces. $s_{X.Y}$, on the other hand, represents the standard deviation for the number of ounces of sugar consumed by any subject who has a specific number of cavities.

The standard error of estimate can be employed to compute a confidence interval for the predicted value of Y (or X). The larger the value of a standard error of estimate, the larger will be the range of values that define the confidence interval and, consequently, the less likely it is that the predicted value Y' (or X') will equal or be close to the actual score of a given subject on that variable.

Equations 28.12 and 28.13 are, respectively, employed to compute the values $s_{Y.X}$ and $s_{X.Y}$ (which are estimates of the underlying population parameters $\sigma_{Y.X}$ and $\sigma_{X.Y}$).

$$s_{Y.X} = \tilde{s}_Y \sqrt{\left[\frac{n-1}{n-2} \right] [1 - r^2]} \quad \text{(Equation 28.12)}$$

$$s_{X.Y} = \tilde{s}_X \sqrt{\left[\frac{n-1}{n-2} \right] [1 - r^2]} \quad \text{(Equation 28.13)}$$

As the size of the sample increases, the value $(n-1)/(n-2)$ in the radical of Equations 28.12 and 28.13 approaches 1, and thus for large sample sizes the equations simplify to $s_{Y.X} = \tilde{s}_Y \sqrt{1 - r^2}$ and $s_{X.Y} = \tilde{s}_X \sqrt{1 - r^2}$. Note, however, that for small sample sizes the latter equations underestimate the values of $s_{Y.X}$ and $s_{X.Y}$.

Equations 28.12 and 28.13 are employed to compute the values $s_{Y.X} = .92$ and $s_{X.Y} = 2.94$.⁸

$$s_{Y.X} = 2.70 \sqrt{\left[\frac{5-1}{5-2} \right] [1 - (.955)^2]} = .92$$

$$s_{X,Y} = 8.58 \sqrt{\left[\frac{5-1}{5-2} \right] [1 - (.955)^2]} = 2.94$$

3. Computation of a confidence interval for the value of the criterion variable⁹ It turns out that Equations 28.12 and 28.13 are not unbiased estimates of error throughout the full range of values the criterion variable may assume. What this translates into is that if a researcher wants to compute a confidence interval with respect to a specific subject's score on the criterion variable, in the interest of complete accuracy an adjusted standard error of estimate value should be employed. The adjusted standard error of estimate values will be designated $\tilde{s}_{Y,X}$ and $\tilde{s}_{X,Y}$. The values computed for $\tilde{s}_{Y,X}$ and $\tilde{s}_{X,Y}$ will always be larger than the values computed for $s_{Y,X}$ and $s_{X,Y}$. The larger the deviation between a subject's score on the predictor variable and the mean score for the predictor variable, the greater the difference between the values $s_{Y,X}$ versus $\tilde{s}_{Y,X}$ and $s_{X,Y}$ versus $\tilde{s}_{X,Y}$. Equations 28.14 and 28.15 are employed to compute the values $\tilde{s}_{Y,X}$ and $\tilde{s}_{X,Y}$.¹⁰ In the latter equations, the values X and Y , respectively, represent the X and Y scores of the specific subject for whom the standard error of estimate is computed.

$$\tilde{s}_{Y,X} = s_{Y,X} \sqrt{1 + \frac{1}{n} + \frac{(X - \bar{X})^2}{SS_X}} \quad \text{(Equation 28.14)}$$

$$\tilde{s}_{X,Y} = s_{X,Y} \sqrt{1 + \frac{1}{n} + \frac{(Y - \bar{Y})^2}{SS_Y}} \quad \text{(Equation 28.15)}$$

At this point two confidence intervals will be computed employing the values $\tilde{s}_{Y,X}$ and $\tilde{s}_{X,Y}$. The two confidence intervals will be in reference to the two subjects for whom the values $Y' = 4.24$ and $X' = 9.02$ are predicted in the previous section (employing Equations 28.4 and 28.8). Initially, the use of Equation 28.14 will be demonstrated to compute a confidence interval for the subject who consumes 10 ounces of sugar (i.e., $X = 10$), and (through use of Equation 28.4) is predicted to have $Y' = 4.24$ cavities. Equation 28.16 is employed to compute a confidence interval for the predicted value of Y .

$$CI_{(1-\alpha)} = Y' \pm (t_{\alpha/2})(\tilde{s}_{Y,X}) \quad \text{(Equation 28.16)}$$

Where: $t_{\alpha/2}$ represents the tabled critical two-tailed value in the t distribution, for $df = n - 2$, below which a proportion (percentage) equal to $[1 - (\alpha/2)]$ of the cases falls. If the proportion (percentage) of the distribution that falls within the confidence interval is subtracted from 1 (100%), it will equal the value of α .

In the computation of a confidence interval, the predicted value Y' can be conceptualized as the mean value in a population of scores on the Y variable for a specific subject. When the sample size employed for the analysis is large (i.e., $n > 100$), one can assume that the shape of such a distribution for each subject will be normal and, in such a case, the relevant tabled critical two-tailed z value (i.e., $z_{\alpha/2}$) can be employed in Equation 28.16 in place of the relevant tabled critical t value. For smaller sample sizes (as is the case for Example 28.1), however, the t distribution provides a more accurate approximation of the underlying population distribution. Use of the normal distribution with small sample sizes underestimates the range of values that define a confidence interval. Inspection of Equation 28.16 reveals that the range of values computed for a confidence interval is a function of the magnitude of the standard error of estimate and the tabled critical t value (the magnitude of the latter being inversely related to the sample size).

In order to use Equation 28.16, the value $\tilde{s}_{Y.X}$ must be computed with Equation 28.14. Employing Equation 28.14, the value $\tilde{s}_{Y.X} = 1.02$ is computed. Note that the latter value is slightly larger than the value $s_{Y.X} = .92$ computed with Equation 28.12.

$$\tilde{s}_{Y.X} = .92 \sqrt{1 + \frac{1}{5} + \frac{(10 - 7.2)^2}{294.8}} = 1.02$$

To demonstrate the use of Equation 28.16, the 95% confidence interval will be computed. The value $t_{.05} = 3.18$ is employed to represent $t_{\alpha/2}$, since in [Table A2](#) it is the tabled critical two-tailed .05 t value for $df = 3$. The appropriate values are now substituted in Equation 28.16 to compute the 95% confidence interval.

$$CI_{.95} = 4.24 \pm (3.18)(1.02) = 4.24 \pm 3.24$$

This result indicates that the researcher can be 95% confident (or the probability is .95) that the number of cavities the subject actually has falls within the range 1.00 and 7.48 (i.e., $1.00 \leq Y \leq 7.48$).

A confidence interval will now be computed for the subject who has 4 cavities (i.e., $Y = 4$), and (through use of Equation 28.8) is predicted to eat 9.02 ounces of sugar. Equation 28.17 is employed to compute a confidence interval for the value of X .

$$CI_{(1 - \alpha)} = X' \pm (t_{\alpha/2})(\tilde{s}_{X.Y}) \quad \text{(Equation 28.17)}$$

In order to use Equation 28.17 the value $\tilde{s}_{X.Y}$ must be computed with Equation 28.15. Employing Equation 28.15, the value $\tilde{s}_{X.Y} = 3.24$ is computed. Note that the latter value is slightly larger than the value $s_{X.Y} = 2.94$ computed with Equation 28.13.

$$\tilde{s}_{X.Y} = 2.94 \sqrt{1 + \frac{1}{5} + \frac{(4 - 3.4)^2}{29.2}} = 3.24$$

As is done in the previous example, the 95% confidence interval will be computed. Thus, the values $t_{.05} = 3.18$ and $\tilde{s}_{X.Y} = 3.24$ are substituted in Equation 28.17.

$$CI_{.95} = 9.02 \pm (3.18)(3.24) = 9.02 \pm 10.30$$

This result indicates that the researcher can be 95% confident (or the probability is .95) that the number of ounces of sugar the subject actually eats falls within the range -1.28 and 19.32 (i.e., $-1.28 \leq X \leq 19.32$). Since it is impossible to have a negative number of ounces of sugar, the result translates into between 0 and 19.32 ounces of sugar.

4. Computation of a confidence interval for a Pearson product-moment correlation coefficient In order to compute a confidence interval for a computed value of the **Pearson product-moment correlation coefficient**, it is necessary to employ a procedure developed by Fisher (1921) referred to as **Fisher's z_r (or z) transformation**. The latter procedure transforms an r value to a scale that is based on the normal distribution. The rationale behind the use of **Fisher's z_r transformation** is that although the theoretical sampling distribution of the correlation coefficient can be approximated by the normal distribution when the value of a population correlation is equal to zero, as the value of the population correlation deviates from zero, the

sampling distribution becomes more and more skewed. Thus, in computing confidence intervals (as well as in testing hypotheses involving one or more populations in which a hypothesized population correlation is some value other than zero), **Fisher's z_r transformation** is required to transform a skewed sampling distribution into a normalized format.

Equation 28.18 is employed to convert an r value into a **Fisher transformed value**, which is represented by the notation z_r .

$$z_r = \frac{1}{2} \ln \left[\frac{1 + r}{1 - r} \right] \quad (\text{Equation 28.18})$$

Where: \ln represents the **natural logarithm** of a number (which is defined in Endnote 5 in the **Introduction**)

Although logarithmic values can be computed with a function key on most scientific calculators, if one does not have access to a calculator, **Table A17 (Table of Fisher's z_r Transformation)** in the **Appendix** provides an alternative way of deriving the Fisher transformed values. The latter table contains the z_r values that correspond to specific values of r . The reader should take note of the fact that in employing Equation 28.18 or **Table A17**, the sign assigned to a z_r value is always the same as the sign of the r value upon which it is based. Thus, a positive r value will always be associated with a positive z_r value, and a negative r value will always be associated with a negative z_r value. When $r = 0$, z_r will also equal zero.

Equation 28.19 is employed to compute the confidence interval for a computed r value.

$$CI_{z_{r(1-\alpha)}} = z_r \pm (z_{\alpha/2}) \sqrt{\frac{1}{n-3}} \quad (\text{Equation 28.19})$$

Where: $z_{\alpha/2}$ represents the tabled critical two-tailed value in the normal distribution below which a proportion (percentage) equal to $[1 - (\alpha/2)]$ of the cases fall. If the proportion (percentage) of the distribution that falls within the confidence interval is subtracted from 1 (100%), it will equal the value of α .

The value $\sqrt{1/(n-3)}$ in Equation 28.19 represents the standard error of z_r . In employing Equation 28.19 to compute the 95% confidence interval, the product of the tabled critical two-tailed .05 z value and the standard error of z_r are added to and subtracted from the Fisher transformed value for the computed r value. The two resulting values, which represent z_r values, are then reconverted into correlation coefficients through use of **Table A17** or by reconfiguring Equation 28.18 to solve for r .¹¹ Use of **Table A17** for the latter is accomplished by identifying the r values which correspond to the computed z_r values. The resulting r values derived from the table identify the limits that define the 95% confidence interval.

Equation 28.19 will now be used to compute the 95% confidence interval for $r = .955$. From **Table A17** it is determined that the Fisher transformed value which corresponds to $r = .955$ is $z_r = 1.886$. The latter value can also be computed with Equation 28.18: $z_r = (1/2)\ln[(1 + .955)/(1 - .955)] = 1.886$. The appropriate values are now substituted in Equation 28.19.

$$CI_{z_{r(.95)}} = 1.886 \pm (1.96) \sqrt{\frac{1}{5-3}} = 1.886 \pm 1.386$$

Subtracting from and adding 1.386 to 1.886, yields the values .5 and 3.272. The latter values are now converted into r values through use of [Table A17](#). By interpolating, we can determine that a z_r value of .5 corresponds to the value $r = .462$, which will define the lower limit of the confidence interval. Since the value $z_r = 3.272$ is substantially above the z value that corresponds to the largest tabled r value, it will be associated with the value $r = 1$. Thus, we can be 95% confident (or the probability is .95) that the true value of the population correlation falls between .462 and 1. Symbolically, this can be written as follows: $.462 \leq \rho \leq 1$. Note that because of the small sample size employed in the experiment, the range of values that define the confidence interval is quite large.

If the 99% confidence interval is computed, the tabled critical two-tailed .01 value $z_{.01} = 2.58$ is employed in Equation 28.19 in place of $z_{.05} = 1.96$. As is always the case in computing a confidence interval, the range of values that defines a 99% confidence interval will be larger than the range which defines a 95% confidence interval.

5. Test 28b: Test for evaluating the hypothesis that the true population correlation is a specific value other than zero In certain instances, a researcher may want to evaluate whether an obtained correlation could have come from a population in which the true correlation between two variables is a specific value other than zero. The null and alternative hypotheses that are evaluated under such conditions are as follows.

$$H_0: \rho = \rho_0$$

(In the underlying population the sample represents, the correlation between the scores of subjects on Variable X and Variable Y equals ρ_0 .)

$$H_1: \rho \neq \rho_0$$

(In the underlying population the sample represents, the correlation between the scores of subjects on Variable X and Variable Y equals some value other than ρ_0 . The alternative hypothesis as stated is **nondirectional**, and is evaluated with a **two-tailed test**. It is also possible to state the alternative hypothesis directionally ($H_1: \rho > \rho_0$ or $H_1: \rho < \rho_0$), in which case it is evaluated with a one-tailed test.)

Equation 28.20 is employed to evaluate the null hypothesis $H_0: \rho = \rho_0$.

$$z = \frac{z_r - z_{\rho_0}}{\sqrt{\frac{1}{n-3}}} \quad \text{(Equation 28.20)}$$

Where: z_r represents the Fisher transformed value of the computed value of r
 z_{ρ_0} represents the Fisher transformed value of ρ_0 , the hypothesized population correlation

Equation 28.20 will now be employed in reference to Example 28.1. Let us assume that we want to evaluate whether the true population correlation between the number of ounces of sugar consumed and the number of cavities is .80. Thus, the null hypothesis is $H_0: \rho = .80$, and the nondirectional alternative hypothesis is $H_1: \rho \neq .80$.

By employing [Table A17](#) (or Equation 28.18), we determine that the corresponding z_r values for the obtained correlation coefficient $r = .955$ and the hypothesized population correlation coefficient $\rho = .80$ are, respectively, $z_r = 1.886$ and $z_{\rho} = 1.099$ (the notation z_{ρ} is

employed in place of z_r , whenever the relevant element in an equation identifies a population correlation). Substituting the Fisher transformed values in Equation 28.20, the value $z = 1.11$ is computed.¹²

$$z = \frac{1.886 - 1.099}{\sqrt{\frac{1}{(5 - 3)}}} = 1.11$$

The computed value $z = 1.11$ is evaluated with **Table A1 (Table of the Normal Distribution)** in the **Appendix**. In order to reject the null hypothesis, the obtained absolute value of z must be equal to or greater than the tabled critical two-tailed value at the prespecified level of significance. Since $z = 1.11$ is less than the tabled critical two-tailed values $z_{.05} = 1.96$ and $z_{.01} = 2.58$, the null hypothesis cannot be rejected at either the .05 or .01 level. Thus, the null hypothesis that the true population correlation equals .80 is retained.

If the alternative hypothesis is stated directionally, in order to reject the null hypothesis the obtained absolute value of z must be equal to or greater than the tabled critical one-tailed value at the prespecified level of significance (i.e., $z_{.05} = 1.65$ or $z_{.01} = 2.33$). Since $z = 1.11$ is less than $z_{.05} = 1.65$, the directional alternative hypothesis $H_0: \rho > .80$ is not supported. Note that the sign of the value of z computed with Equation 28.20 will be positive when the computed value of r is greater than the hypothesized value ρ_0 , and negative when the computed value of r is less than the hypothesized value ρ_0 . Since $r = .955$ is a positive number, the directional alternative hypothesis $H_0: \rho < .80$ is inconsistent with the data, and is thus not supported.

6. Computation of power for the Pearson product-moment correlation coefficient Prior to collecting correlational data, a researcher can determine the likelihood of detecting a population correlation of a specific magnitude if a specific value of n is employed. As a result of such a power analysis, one can determine the minimum sample size required to detect a prespecified population correlation. To illustrate the computation of power, let us assume that prior to collecting the data for 25 subjects a researcher wants to determine the power associated with the analysis if the value of the population correlation he wants to detect is $\rho = .40$.¹³ It will be assumed that a nondirectional analysis is conducted, with $\alpha = .05$.

Equation 28.21 (which is described in Guenther (1965, pp. 244–246)) is employed to compute the power of the analysis.

$$\delta = |z_{\rho_0} - z_{\rho_1}| \sqrt{n - 3} \quad \text{(Equation 28.21)}$$

Where: z_{ρ_0} is the **Fisher transformed value** of the population correlation stipulated in the null hypothesis, and z_{ρ_1} is the **Fisher transformed value** of the population correlation the researcher wants to detect

Table A17 in the **Appendix** reveals that the Fisher transformed value associated with $\rho = 0$ is $z_{\rho_0} = z_{\rho_0} = 0$, and thus when the null hypothesis $H_0: \rho = 0$ is employed (which it will be assumed is the case), Equation 28.21 reduces to $\delta = z_{\rho_1} \sqrt{n - 3}$.

Employing **Table A17**, we determine that the Fisher transformed value for the population correlation of $\rho = .40$ is $z_{\rho_1} = .424$. Substituting the appropriate values in Equation 28.21, the value $\delta = 1.99$ is computed.

$$\delta = |0 - .424| \sqrt{25 - 3} = 1.99$$

The obtained value $\delta = 1.99$ is evaluated with **Table A3 (Power Curves for Student's t Distribution)** in the **Appendix**. A full discussion on the use of **Table A3** (which is employed to evaluate the power of a number of different types of t tests) can be found in Section VI of the **single-sample t test (Test 2)**. Employing the power curve for $df = \infty$ in **Table A3-C** (the appropriate table for a nondirectional/two-tailed analysis, with $\alpha = .05$), we determine the power of the correlational analysis to be approximately .52.¹⁴ Thus, if the underlying population correlation is $\rho = .40$ and a sample size of $n = 25$ is employed, the likelihood of the researcher rejecting the null hypothesis is only .52. If this value is deemed too small, the researcher can substitute larger values of n in Equation 28.21 until a value is computed for δ that is associated with an acceptable level of power.

Equation 28.21 can also be employed if the value stated in the null hypothesis is some value other than $\rho = 0$. Assume that a number of studies suggest that the population correlation between two variables is $\rho = .60$. A researcher, who has reason to believe that the latter value may overestimate the true population correlation, wants to compute the power of a correlational analysis to determine if the true population correlation is, in fact, $\rho = .40$. In this example (for which the value $n = 25$ will be employed) $H_0: \rho = .60$. Since the researcher believes the true population correlation may be less than .60, the alternative hypothesis is stated directionally. Thus, $H_1: \rho < .60$.

Employing **Table A17**, we determine the Fisher transformed value for $\rho = .60$ is $z_\rho = .693$ and, from the previous analysis, we know that for $\rho = .40$, $z_\rho = .424$. Substituting the appropriate values in Equation 28.21, the value $\delta = 1.26$ is computed.

$$\delta = |.693 - .424| \sqrt{25 - 3} = 1.26$$

Employing the power curve for $df = \infty$ in **Table A3-D** (i.e., the curves for the one-tailed .05 value), we determine the power of the analysis to be approximately .37. Thus, if the underlying population correlation is $\rho = .40$ and a sample size of $n = 25$ is employed, the likelihood of the researcher rejecting the null hypothesis $H_0: \rho = .60$ is only .37.

Cohen (1977; 1988, Chapter 3) has derived tables that allow a researcher to determine the appropriate sample size to employ if one wants to evaluate an alternative hypothesis which designates a specific value for a population correlation (when the null hypothesis is $H_0: \rho = 0$). These tables can be employed as an alternative to the procedure described in this section in computing power for the **Pearson product-moment correlation coefficient**.

7. Test 28c: Test for evaluating a hypothesis on whether there is a significant difference between two independent correlations There are occasions when a researcher will compute a correlation between the same two variables for two independent samples. In the event the correlation coefficients obtained for the two samples are not equal, the researcher may wish to determine whether the difference between the two correlations is statistically significant. The null and alternative hypotheses that are evaluated under such conditions are as follows.

$$H_0: \rho_1 = \rho_2$$

(In the underlying populations represented by the two samples, the correlation between the two variables is equal.)

$$H_1: \rho_1 \neq \rho_2$$

(In the underlying populations represented by the two samples, the correlation between the two variables is not equal. The alternative hypothesis as stated is **nondirectional**, and is evaluated

with a **two-tailed test**. It is also possible to state the alternative hypothesis directionally ($H_1: \rho_1 > \rho_2$ or $H_1: \rho_1 < \rho_2$), in which case it is evaluated with a one-tailed test.)

To illustrate, let us assume that in Example 28.1 the correlation of $r = .955$ between the number of ounces of sugar eaten per week and the number of cavities is based on a sample of five ten-year old boys (to be designated Sample 1). Let us also assume that the researcher evaluates a sample of five ten-year old girls (to be designated Sample 2), and determines that in this second sample the correlation between the number of ounces of sugar eaten per week and the number of cavities is $r = .765$. Equation 28.22 can be employed to determine whether or not the difference between $r_1 = .955$ and $r_2 = .765$ is significant.

$$z = \frac{z_{r_1} - z_{r_2}}{\sqrt{\frac{1}{n_1 - 3} + \frac{1}{n_2 - 3}}} \quad \text{(Equation 28.22)}$$

Where: z_{r_1} represents the Fisher transformed value of the computed value of r_1 for Sample 1
 z_{r_2} represents the Fisher transformed value of the computed value of r_2 for Sample 2
 n_1 and n_2 are, respectively, the number of subjects in Sample 1 and Sample 2

Since there are five subjects in both samples, $n_1 = n_2 = 5$. From the analysis in the previous section we already know that the Fisher transformed value of $r_1 = .955$ is $z_{r_1} = 1.886$. For the female sample, employing [Table A17](#) we determine that the Fisher transformed value of $r_2 = .765$ is $z_{r_2} = 1.008$. When the appropriate values are substituted in Equation 28.22, they yield the value $z = .878$.

$$z = \frac{1.886 - 1.008}{\sqrt{\frac{1}{5 - 3} + \frac{1}{5 - 3}}} = .878$$

The value $z = .878$ is evaluated with [Table A1](#). In order to reject the null hypothesis, the obtained absolute value of z must be equal to or greater than the tabled critical two-tailed value at the prespecified level of significance. Since $z = .878$ is less than the tabled critical two-tailed values $z_{.05} = 1.96$ and $z_{.01} = 2.58$, the nondirectional alternative hypothesis $H_1: \rho_1 \neq \rho_2$ is not supported at either the .05 or .01 level. Thus, we retain the null hypothesis that there is an equal correlation between the two variables in each of the populations represented by the samples.

If the alternative hypothesis is stated directionally, in order to reject the null hypothesis the obtained absolute value of z must be equal to or greater than the tabled critical one-tailed value at the prespecified level of significance (i.e., $z_{.05} = 1.65$ or $z_{.01} = 2.33$). The sign of z will be positive when $r_1 > r_2$, and thus can only support the alternative hypothesis $H_1: \rho_1 > \rho_2$. The sign of z will be negative when $r_1 < r_2$, and thus can only support the alternative hypothesis $H_1: \rho_1 < \rho_2$. Since $z = .878$ is less than $z_{.05} = 1.65$, the directional alternative hypothesis $H_1: \rho_1 > \rho_2$ is not supported.

Edwards (1984) notes that when the null hypothesis is retained, since the analysis suggests that the two samples represent a single population, Equation 28.23 can be employed to provide a weighted estimate of the common population correlation.

$$\bar{z}_r = \frac{(n_1 - 3)z_{r_1} + (n_2 - 3)z_{r_2}}{(n_1 - 3) + (n_2 - 3)} \quad (\text{Equation 28.23})$$

Substituting the data in Equation 28.23, the Fisher transformed value $\bar{z}_r = 1.447$ is computed.

$$\bar{z}_r = \frac{(5 - 3)(1.886) + (5 - 3)(1.008)}{(5 - 3) + (5 - 3)} = 1.447$$

Employing **Table A17**, we determine that the Fisher transformed value $z_r = 1.447$ corresponds to the value $r = .895$. Thus, $r = .895$ can be employed as the best estimate of the common population correlation. Note that the estimated common population correlation computed with Equation 28.23 is not the same value that is obtained if, instead, one calculates the weighted average of the two correlations (which, since the sample sizes are equal, is the average of the two correlations: $(.955 + .765)/2 = .86$). The fact that the weighted average of the two correlations yields a different value from the result obtained with Equation 28.23 can be attributed to fact that the theoretical sampling distribution of the correlation coefficient becomes more skewed as the absolute value of r approaches 1.

Cohen (1977; 1988, Ch. 4) has developed a statistic referred to as the ***q* index** that can be employed for computing the power of the test comparing two independent correlation coefficients. A brief discussion of the ***q* index** can be found in Section IX (the **Addendum**) under the discussion of **meta-analysis and related topics**.

8. Test 28d: Test for evaluating a hypothesis on whether k independent correlations are homogeneous **Test 28c** can be extended to determine whether more than two independent correlation coefficients are homogeneous (in other words, can be viewed as representing the same population correlation, ρ). The null and alternative hypotheses that are evaluated under such conditions are as follows.

$$H_0: \rho_1 = \rho_2 = \dots = \rho_k$$

(In the underlying populations represented by the k samples, the correlation between the two variables is equal.)

$$H_1: \text{Not } H_0$$

(In the underlying populations represented by the k samples, the correlation between the two variables is not equal in at least two of the populations. The alternative hypothesis as stated is **nondirectional**.)

To illustrate, let us assume that the correlation between the number of ounces of sugar eaten per week and the number of cavities is computed for three independent samples, each sample consisting of five children living in different parts of the country. The values of the correlations obtained for the three samples are as follows: $r_1 = .955$, $r_2 = .765$, $r_3 = .845$.

Equation 28.24 is employed to determine whether the $k = 3$ sample correlations are homogeneous. (Equation 28.89 in Section IX (the **Addendum**) is a different but equivalent version of Equation 28.24.) In Equation 28.24, wherever the summation sign $\sum_{j=1}^k$ appears it indicates that the operation following the summation sign is carried out for each of the $k = 3$ samples, and the resulting $k = 3$ values are summed.

$$\chi^2 = \sum_{j=1}^k [(n_j - 3) z_{r_j}^2] - \frac{\left[\sum_{j=1}^k (n_j - 3) z_{r_j} \right]^2}{\sum_{j=1}^k (n_j - 3)} \quad (\text{Equation 28.24})$$

Since there are five subjects in each sample, $n_1 = n_2 = n_3 = 5$. From the analysis in the previous section, we already know that the Fisher transformed values of $r_1 = .955$ and $r_2 = .765$ are, respectively, $z_{r_1} = 1.886$ and $z_{r_2} = 1.008$. Employing [Table A17](#), we determine for Sample 3 the Fisher transformed value of $r_3 = .845$ is $z_{r_3} = 1.238$. When the appropriate values are substituted in Equation 28.24, they yield the value $\chi^2 = .83$.

$$\begin{aligned} \chi^2 &= [(5 - 3)(1.886)^2 + (5 - 3)(1.008)^2 + (5 - 3)(1.238)^2] \\ &\quad - \frac{[(5 - 3)(1.886) + (5 - 3)(1.008) + (5 - 3)(1.238)]^2}{(5 - 3) + (5 - 3) + (5 - 3)} = .83 \end{aligned}$$

The value $\chi^2 = .83$ is evaluated with [Table A4 \(Table of the Chi-Square Distribution\)](#) in the **Appendix**. The degrees of freedom employed in evaluating the obtained chi-square value are $df = k - 1$. Thus, for the above example, $df = 3 - 1 = 2$. In order to reject the null hypothesis, the obtained value of χ^2 must be equal to or greater than the tabled critical value at the prespecified level of significance. Since $\chi^2 = .83$ is less than $\chi_{.05}^2 = 5.99$ and $\chi_{.01}^2 = 9.21$ (which are the tabled critical .05 and .01 values for $df = 2$ when a nondirectional alternative hypothesis is employed), the null hypothesis cannot be rejected at either the .05 or .01 level. Thus, we retain the null hypothesis that in the underlying populations represented by the $k = 3$ samples, the correlations between the two variables are equal.¹⁵

Edwards (1984) notes that when the null hypothesis is retained, since the analysis suggests that the k samples represent a single population, Equation 28.25 can be employed to provide a weighted estimate of the common population correlation.¹⁶

$$\bar{z}_r = \frac{\sum_{j=1}^k (n_j - 3) z_{r_j}}{\sum_{j=1}^k (n_j - 3)} \quad (\text{Equation 28.25})$$

Substituting the data in Equation 28.25, the Fisher transformed value $\bar{z}_r = 1.377$ is computed.

$$\bar{z}_r = \frac{(5 - 3)(1.886) + (5 - 3)(1.008) + (5 - 3)(1.238)}{(5 - 3) + (5 - 3) + (5 - 3)} = 1.377$$

Employing [Table A17](#), we determine that the Fisher transformed value $z_r = 1.377$ corresponds to the value $r = .88$. Thus, $r = .88$ can be employed as the best estimate of the common population correlation. Note that, as is the case when the same analysis is conducted for $k = 2$ samples, the value obtained for the common population correlation (using Equation 28.25) is not the same as the value that is obtained if the weighted average of the three correlation coefficients is computed (i.e., $(.955 + .765 + .845)/3 = .855$).

9. Test 28e: Test for evaluating the null hypothesis $H_0: \rho_{XZ} = \rho_{YZ}$ There are instances when a researcher may want to evaluate if, within a specific population, one variable (X) has the same correlation with some criterion variable (Z) as does another variable (Y). The null and alternative hypotheses which are evaluated in such a situation are as follows.

$$H_0: \rho_{XZ} = \rho_{YZ}$$

(In the underlying population represented by the sample, the correlation between variables X and Z is equal to the correlation between variables Y and Z .)

$$H_1: \rho_{XZ} \neq \rho_{YZ}$$

(In the underlying population represented by the sample, the correlation between variables X and Z is not equal to the correlation between variables Y and Z . The alternative hypothesis as stated is **nondirectional**, and is evaluated with a **two-tailed test**. It is also possible to state the alternative hypothesis directionally ($H_1: \rho_{XZ} > \rho_{YZ}$ or $H_1: \rho_{XZ} < \rho_{YZ}$), in which case it is evaluated with a one-tailed test.)

To illustrate how one can evaluate the null hypothesis $H_0: \rho_{XZ} = \rho_{YZ}$, let us assume that the correlation between the number of ounces of sugar eaten per week and the number of cavities is computed for five subjects, and $r = .955$. Let us also assume that for the same five subjects we determine that the correlation between the number of ounces of salt eaten per week and the number of cavities is $r = .52$. We want to determine whether there is a significant difference in the correlation between the number of ounces of sugar eaten per week and the number of cavities versus the number of ounces of salt eaten per week and the number of cavities. Let us also assume that for the sample of five subjects, the correlation between the number of ounces of sugar eaten per week and the number of ounces of salt eaten per week is $r = .37$.

In the above example, within the framework of the hypothesis being evaluated we have two predictor variables — the number of ounces of sugar eaten per week and the number of ounces of salt eaten per week. These two predictor variables will, respectively, represent the X and Y variables in the analysis to be described. The number of cavities, which is the criterion variable, will be designated as the Z variable. Thus, $r_{XZ} = .955$, $r_{YZ} = .52$, $r_{XY} = .37$.

The test statistic for evaluating the null hypothesis, which is based on the t distribution, is computed with Equation 28.26. A more detailed description of the test statistic can be found in Steiger (1980), who notes that Equation 28.26 provides a superior test of the hypothesis being evaluated when compared with an alternative procedure developed by Hotelling (1940) (which is described in Lindeman *et al.* (1980)).

(Equation 28.26)

$$t = (r_{YZ} - r_{XZ}) \sqrt{\frac{(n - 1)(1 + r_{XY})}{2 \left[\frac{(n - 1)}{(n - 3)} \right] [1 - r_{YZ}^2 - r_{XZ}^2 - r_{XY}^2 + 2r_{YZ}r_{XZ}r_{XY}] + \left[\frac{r_{YZ} + r_{XZ}}{2} \right]^2 [1 - r_{XY}]^3}}$$

Substituting the values $n = 5$, $r_{XZ} = .955$, $r_{YZ} = .52$, and $r_{XY} = .37$ in Equation 28.26, the value $t = -1.78$ is computed.

$$t = (.52 - .955) \sqrt{\frac{(5-1)(1+.37)}{2 \left[\frac{(5-1)}{(5-3)} \right] [1 - (.52)^2 - (.955)^2 - (.37)^2 + 2(.52)(.955)(.37)] + \left[\frac{(.52 + .955)}{2} \right]^2 [1 - (.37)]^3}}$$

$$= -1.78$$

The value $t = -1.78$ is evaluated with **Table A2**. The degrees of freedom employed in evaluating the obtained t value are $df = n - 3$. Thus, for the above example, $df = 5 - 3 = 2 = 2$. In order to reject the null hypothesis, the obtained absolute value of t must be equal to or greater than the tabled critical value at the prespecified level of significance. Since the absolute value $t = 1.78$ is less than $t_{.05} = 4.30$ and $t_{.01} = 9.93$ (which are the tabled critical two-tailed values for $df = 2$), the null hypothesis cannot be rejected at either the .05 or .01 level. Thus, we retain the null hypothesis that the population correlation between variables X and Z is equal to the population correlation between variables Y and Z .

If the alternative hypothesis is stated directionally, in order to reject the null hypothesis, the obtained absolute value of t must be equal to or greater than the tabled critical one-tailed value at the prespecified level of significance (which for $df = 2$ are $t_{.05} = 2.92$ or $t_{.01} = 6.97$). The sign of t must be positive if $H_1: \rho_{XZ} < \rho_{YZ}$, and must be negative if $H_1: \rho_{XZ} > \rho_{YZ}$. Since the absolute value $t = 1.78$ is less than $t_{.05} = 2.92$, the directional alternative hypothesis $H_1: \rho_{XZ} > \rho_{YZ}$ is not supported.

In the event the t value obtained with Equation 28.26 is significant, it indicates that the predictor variable which correlates highest with the criterion variable (i.e., the one with the highest absolute value) is the best predictor of subjects' scores on the latter variable. It should be noted that because the analysis discussed in this section represents a dependent samples analysis (since all three correlations are based on the same sample), Equation 28.22 (the equation for contrasting two independent correlations) is not appropriate to use to evaluate the null hypothesis $H_0: \rho_{XZ} = \rho_{YZ}$.

10. Tests for evaluating a hypothesis regarding one or more regression coefficients A number of tests have been developed that evaluate hypotheses concerning the slope of a regression line (which is also referred to as a **regression coefficient**). This section will present a brief description of such tests. In the statement of the null and alternative hypotheses of tests concerning a regression coefficient, the notation β is employed to represent the slope of the line in the underlying population represented by a sample. Thus, β_Y is the population regression coefficient of the **regression line of Y on X** , and β_X is the population regression coefficient of the **regression line of X on Y** .

Test 28f: Test for evaluating the null hypothesis $H_0: \beta = 0$ A test of significance can be conducted to evaluate the hypothesis of whether, in the underlying population, the value of the slope of a regression line is equal to zero. The null hypotheses that can be evaluated in reference to the two regression lines are $H_0: \beta_Y = 0$ and $H_0: \beta_X = 0$. In point of fact, the test of the generic null hypothesis $H_0: \beta = 0$ will always yield the same result as that obtained when the null hypothesis $H_0: \rho = 0$ is evaluated using **Test 28a** (which employs Equation 28.3). This is the case, since whenever, $\rho = 0$, the slope of a regression line in the underlying population will also equal zero. Equations 28.27 and 28.28 are, respectively, employed to evaluate the null hypotheses $H_0: \beta_Y = 0$ and $H_0: \beta_X = 0$. The equations are employed below with the data for Example 28.1 and, in both instances, yield the same t value as that obtained when the null hypothesis $H_0: \rho = 0$ is evaluated with Equation 28.3. The slight discrepancies between the t values computed with Equations 28.3, 28.27, and 28.28 are the result of rounding off error.

$$t = \frac{(b_Y)(s_X)\sqrt{n-1}}{s_{Y.X}} = \frac{(.30)(8.58)\sqrt{5-1}}{.92} = 5.60 \quad (\text{Equation 28.27})$$

$$t = \frac{(b_X)(s_Y)\sqrt{n-1}}{s_{X.Y}} = \frac{(3.03)(2.70)\sqrt{5-1}}{2.94} = 5.57 \quad (\text{Equation 28.28})$$

The t values computed with Equations 28.27 and 28.28 are evaluated with [Table A2](#). The degrees of freedom employed in evaluating the obtained t values are $df = n - 2$. Since both t values are identical to the t value computed with Equation 28.3 and the same degrees of freedom are employed, interpretation of the t values leads to the same conclusions — except, in this case, the conclusions are in reference to the regression coefficients β_Y and β_X . Thus, the nondirectional alternative hypotheses $H_1: \beta_Y \neq 0$ and $H_1: \beta_X \neq 0$ are supported at the .05 level, since (for $df = 3$) the computed t values are greater than the tabled critical two-tailed value $t_{.05} = 3.18$. The directional alternative hypotheses $H_1: \beta_Y > 0$ and $H_1: \beta_X > 0$ are supported at both the .05 and .01 levels, since the sign of t (as well as the sign of each of the regression coefficients) is positive, and the computed t values are greater than the tabled critical one-tailed values $t_{.05} = 2.35$ and $t_{.01} = 4.54$.

Equations 28.29 and 28.30 can, respectively, be employed to compute confidence intervals for the regression coefficients β_Y and β_X . The computation of the 95% confidence interval for the two regression coefficients is demonstrated below. The value $t_{.05} = 3.18$ (which is also employed in computing the confidence intervals derived with Equations 28.16 and 28.17) is employed in Equations 28.29 and 28.30 to represent $t_{\alpha/2}$, since in [Table A2](#) it is the tabled critical two-tailed .05 t value for $df = 3$ (which is computed with $df = n - 2$).

(Equation 28.29)

$$CI_{\beta_{Y(1-\alpha)}} = b_Y \pm (t_{\alpha/2}) \left[\frac{s_{Y.X}}{(s_X)\sqrt{n-1}} \right] = .30 \pm (3.18) \left[\frac{.92}{8.58\sqrt{5-1}} \right] = .30 \pm .17$$

(Equation 28.30)

$$CI_{\beta_{X(1-\alpha)}} = b_X \pm (t_{\alpha/2}) \left[\frac{s_{X.Y}}{(s_Y)\sqrt{n-1}} \right] = 3.03 \pm (3.18) \left[\frac{2.94}{2.70\sqrt{5-1}} \right] = 3.03 \pm 1.73$$

The above results indicate the following: a) There is a 95% likelihood that the population regression coefficient β_Y falls within the range .13 and .47 (i.e., $.13 \leq \beta_Y \leq .47$); and b) There is a 95% likelihood that the population regression coefficient β_X falls within the range 1.30 and 4.76 (i.e., $1.30 \leq \beta_X \leq 4.76$). Since the nondirectional alternative hypotheses $H_1: \beta_Y \neq 0$ and $H_1: \beta_X \neq 0$ are supported at the .05 level, it logically follows that the value zero will not fall within the range that defines either of the confidence intervals.

Test 28g: Test for evaluating the null hypothesis $H_0: \beta_1 = \beta_2$ A test of significance can be conducted to evaluate whether the slopes of two regression lines obtained from two independent samples are equal to one another. As is the case with **Test 28c**, it is assumed that the correlations for the independent samples are for the same two variables. The null hypotheses evaluated by the test for the **regression lines of Y on X** and the **regression lines of X on Y** are, respectively, $H_0: \beta_{Y_1} = \beta_{Y_2}$ and $H_0: \beta_{X_1} = \beta_{X_2}$ (where β_{Y_i} represents the slope of the **regression line of Y on X** in the underlying population represented by Sample i , and β_{X_i} represents the slope of the

regression line of X on Y in the underlying population represented by Sample i). As a result of evaluating the null hypothesis in reference to two independent **regression lines of Y on X** , a researcher can determine if the degree of change on the Y variable when the X variable is incremented by one unit is equivalent in the two samples. In the case of two independent **regression lines of X on Y** , a researcher can determine if the degree of change on the X variable when the Y variable is incremented by one unit is equivalent in the two samples. It should be noted that the test employed to evaluate the generic null hypothesis $H_0: \beta_1 = \beta_2$ is not equivalent to **Test 28c**, which evaluates the null hypothesis $H_0: \rho_1 = \rho_2$. This is the case since (as is illustrated in [Figure 28.2](#)) it is entirely possible for the regression lines associated with two independent correlations to have identical slopes, yet be associated with dramatically different correlations.

Equations 28.31 and 28.32 are employed to evaluate the null hypotheses $H_0: \beta_{Y_1} = \beta_{Y_2}$ and $H_0: \beta_{X_1} = \beta_{X_2}$. The t values computed with Equations 28.31 and 28.32 are evaluated with [Table A2](#). The degrees of freedom employed in evaluating the obtained t values are $df = (n_1 - 2) + (n_2 - 2) = n_1 + n_2 - 4$.¹⁷

$$t = \frac{b_{Y_1} - b_{Y_2}}{\sqrt{\frac{s_{Y \cdot X_1}^2}{(\bar{s}_{X_1}^2)(n_1 - 1)} + \frac{s_{Y \cdot X_2}^2}{(\bar{s}_{X_2}^2)(n_2 - 1)}}} \quad \text{(Equation 28.31)}$$

$$t = \frac{b_{X_1} - b_{X_2}}{\sqrt{\frac{s_{X \cdot Y_1}^2}{(\bar{s}_{Y_1}^2)(n_1 - 1)} + \frac{s_{X \cdot Y_2}^2}{(\bar{s}_{Y_2}^2)(n_2 - 1)}}} \quad \text{(Equation 28.32)}$$

Equations 28.31 and 28.32 can be employed to evaluate the regression coefficients associated with the two independent correlations described within the framework of the example employed to demonstrate **Test 28c**. If, for instance, the regression coefficient b_{Y_1} computed for boys (who will represent Sample 1) is larger than the regression coefficient b_{Y_2} computed for girls (who will represent Sample 2), Equation 28.31 can be employed to evaluate the null hypothesis $H_0: \beta_{Y_1} = \beta_{Y_2}$. Although the full analysis will not be done here, the following values would be used in Equation 28.31 for Sample 1/boys (whose data are the same as that employed in Example 28.1): $n_1 = 5$, $b_{Y_1} = .30$, $\bar{s}_{X_1}^2 = (8.58)^2 = 73.62$, $s_{Y \cdot X_1}^2 = (.92)^2 = .85$. If upon substituting the analogous values for a sample of five girls in Equation 28.31 the resulting t value is significant, the null hypothesis $H_0: \beta_{Y_1} = \beta_{Y_2}$ is rejected. The number of degrees of freedom employed for the analysis are $df = 5 + 5 - 4 = 6$. The tabled critical .05 and .01 two-tailed and one-tailed t values for $df = 6$ are, respectively, $t_{.05} = 2.45$ and $t_{.01} = 3.71$, and $t_{.05} = 1.94$ and $t_{.01} = 3.14$. If the nondirectional alternative hypothesis $H_1: \beta_{Y_1} \neq \beta_{Y_2}$ is employed, in order to be significant the obtained absolute value of t must be equal to or greater than the tabled critical two-tailed value at the prespecified level of significance. If the directional alternative hypothesis $H_1: \beta_{Y_1} > \beta_{Y_2}$ is employed, in order to be significant the computed t value must be a positive number that is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance. If the directional alternative hypothesis $H_1: \beta_{Y_1} < \beta_{Y_2}$ is employed, in order to be significant, the computed t value must be a negative number that has an absolute value which is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.¹⁸

11. Additional correlational procedures At the conclusion of the discussion of the **Pearson product-moment correlation coefficient**, an **Addendum** (Section IX) has been included which provides a description of the following additional correlational procedures that are directly or indirectly related to the **Pearson product-moment correlation coefficient**: a) **Test 28h: The point-biserial correlation coefficient**; b) **Test 28i: The biserial correlation coefficient**; c) **Test 28j: The tetrachoric correlation coefficient**; d) **Test 28k: The multiple correlation coefficient**; e) **Test 28l: The partial correlation coefficient**; f) **Test 28m: The semi-partial correlation coefficient**. The **Addendum** also contains additional material that is relevant to the general subject of correlation.

VII. Additional Discussion of the Pearson Product-Moment Correlation Coefficient

1. The definitional equation for the Pearson product-moment correlation coefficient

Although more computationally tedious than Equation 28.1, Equation 28.33 is a conceptually more meaningful equation for computing the **Pearson product-moment correlation coefficient**. Unlike Equation 28.1, which allows for the quick computation of r , Equation 28.33 reveals the fact that Pearson conceptualized the product-moment correlation coefficient as the average of the products of the paired z scores of subjects on the X and Y variables.

$$r = \frac{\sum_{i=1}^n z_{X_i} z_{Y_i}}{n - 1} \quad (\text{Equation 28.33})$$

Where: $z_{X_i} = (X_i - \bar{X})/\bar{s}_X$ and $z_{Y_i} = (Y_i - \bar{Y})/\bar{s}_Y$, with X_i and Y_i representing the scores of the i^{th} subject on the X and Y variables

As noted above, the correlation coefficient is, in actuality, the mean of the product of each subject's X and Y scores, when the latter are expressed as z scores. Since the computed r value represents an average score, many books employ n as the denominator of Equation 28.33 instead of $(n - 1)$. In point of fact, n can be employed as the denominator of Equation 28.33 if, in computing the z_{X_i} and z_{Y_i} scores, the sample standard deviations s_X and s_Y (computed with Equation I.7) are employed in place of the estimated population standard deviations \bar{s}_X and \bar{s}_Y (computed with Equation I.8). When the estimated population standard deviations are employed, however, $(n - 1)$ is the appropriate value to employ in the denominator of Equation 28.33.

In employing Equation 28.33 to compute the value of r , initially the mean and estimated population standard deviation of the X and Y scores must be computed. Each X score is then converted into a z score by employing the equation for converting a raw score into a z score (i.e., $z_{X_i} = (X_i - \bar{X})/\bar{s}_X$). Each Y score is also converted into a z score using the same equation with reference to the Y variable (i.e., $z_{Y_i} = (Y_i - \bar{Y})/\bar{s}_Y$).¹⁹ The product of each subject's z_{X_i} and z_{Y_i} score is obtained, and the sum of the products for the n subjects is computed. The latter sum is divided by $(n - 1)$, yielding the value of r which represents an average of the sum of the products.²⁰ The value of r computed with Equation 28.33 will be identical to that computed with Equation 28.1.

The computation of the value $r = .955$ with Equation 28.33 is demonstrated in [Table 28.2](#). In deriving the z_{X_i} and z_{Y_i} scores, the following summary values are employed: $\bar{X} = 7.2$, $\bar{s}_X = 8.58$, $\bar{Y} = 3.4$, $\bar{s}_Y = 2.70$. Equation 28.33 yields the value $r = 3.818/4 = .955$ when the sum of the products in the last column of [Table 28.2](#) is divided by $(n - 1)$.

Table 28.2 Computation of r with Equation 28.33

X_i	$z_{X_i} = \frac{X_i - \bar{X}}{\bar{s}_X}$	Y	$z_{Y_i} = \frac{Y_i - \bar{Y}}{\bar{s}_Y}$	$z_{X_i}z_{Y_i}$
20	1.49	7	1.33	1.982
0	-.84	0	-1.26	1.058
1	-.72	2	-.52	.374
12	.56	5	.59	.330
3	-.49	3	-.15	.074
				$\Sigma z_{X_i}z_{Y_i} = 3.818$

2. Residuals In Section VI it is noted that a **residual** is the difference between the predicted value of a subject's score on the criterion variable and the subject's actual score on the criterion variable. Thus, a residual indicates the amount of error between a subject's actual and predicted scores. If e_i represents the amount of error for the i^{th} subject, the residual for a subject can be defined as follows (assuming the **regression line of Y on X** is employed): $e_i = (Y_i - Y_i')$. In the least squares regression model, the sum of the residuals will always equal zero. Thus, $\Sigma_{i=1}^n e_i = \Sigma_{i=1}^n (Y_i - Y_i') = 0$. Since the sum of the residuals equals zero, the average of the residuals will also equal zero (i.e., $\bar{e}_i = (\Sigma_{i=1}^n e_i)/n = 0$). The latter reflects the fact that for some of the subjects the predicted value of Y_i' will be larger than Y_i , while for other subjects the predicted value of Y_i' will be smaller than Y_i (of course, for some subjects Y_i' may equal Y_i). It should be noted that if the sum of the squared distances of the data points from the regression line is not the minimum possible value, the sum of the residuals will be some value other than zero.

$\Sigma_{i=1}^n e_i^2 = \Sigma_{i=1}^n (Y_i - Y_i')^2$ (which is the sum of the squared residuals) provides an index of the accuracy of prediction that results from use of the regression equation. When the sum of the squared residuals is small, prediction will be accurate but when it is large, prediction will be inaccurate. When the sum of the squared residuals equals zero (which will only be the case when $|r| = 1$), prediction will be perfect. The latter statement, however, only applies to the scores of subjects in the sample employed in the study. It does not ensure that prediction will be perfect for other members of the underlying population the sample represents. The accuracy of prediction for the population will depend upon the degree to which the derived regression equation is an accurate estimate of the actual regression equation in the underlying population.

The partitioning of the variation on the criterion variable in the least squares regression model can be summarized by Equation 28.34.

$$\sum_{i=1}^n (Y_i - \bar{Y})^2 = \sum_{i=1}^n (Y_i' - \bar{Y})^2 + \sum_{i=1}^n (Y_i - Y_i')^2 \quad (\text{Equation 28.34})$$

Total variation = Explained variation + Error variation

Note that in Equation 28.34, the error (unexplained) variation is the sum of the squared residuals. When $|r| = 1$, $\Sigma_{i=1}^n (Y_i - Y_i')^2 = 0$, which as noted earlier results in perfect prediction. When, on the other hand, $r = 0$, $\Sigma_{i=1}^n (Y_i' - \bar{Y})^2 = 0$, and thus the value \bar{Y} will be the predicted value of Y' for each subject (since, using Equations 28.6 and 28.7, if $r = 0$, $b_Y = 0$ and $a_Y = \bar{Y}$. If $a_Y = \bar{Y}$, the value of Y' computed with Equation 28.4 is $Y' = \bar{Y}$).

Through use of the residuals, the **coefficient of determination** can be expressed with Equation 28.35.

$$r^2 = \frac{\text{Explained variation}}{\text{Total variation}} = \frac{\sum_{i=1}^n (Y_i' - \bar{Y})^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2} \quad (\text{Equation 28.35})$$

Equation 28.36 (which is the square root of Equation 28.35) represents an alternative (albeit more tedious) way of computing the correlation coefficient.

$$r = \pm \sqrt{\frac{\sum_{i=1}^n (Y_i' - \bar{Y})^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2}} \quad (\text{Equation 28.36})$$

The value $s_{Y.X}^2$ is the **residual variance** (i.e., the variance of the residuals). The residual variance (which is the square of the value $s_{Y.X}$ computed with Equation 28.12) can be defined by Equation 28.37. The denominator of Equation 28.37 represents the degrees of freedom employed in the analysis.

$$s_{Y.X}^2 = \frac{\sum_{i=1}^n (Y_i - Y_i')^2}{n - 2} \quad (\text{Equation 28.37})$$

Equation 28.38, which is the square root of Equation 28.37, is an alternative (albeit more tedious) way of computing the **standard error of estimate**. Inspection of Equation 28.38 reveals that the greater the sum of the squared residuals, the greater the value of $s_{Y.X}$.

$$s_{Y.X} = \sqrt{\frac{\sum_{i=1}^n (Y_i - Y_i')^2}{n - 2}} \quad (\text{Equation 28.38})$$

Everything that has been said about the residuals with reference to the **regression line of Y on X** can be generalized to the **regression line of X on Y** (in which case the residual for each subject is represented by $e_i = (X_i - X_i')$). Thus, all of the equations described in this section can be generalized to the second regression line by respectively employing the values X_i , X_i' , and \bar{X} in place of Y_i , Y_i' , and \bar{Y} .

3. Covariance In Section IV it is noted that the numerator of Equation 28.1 is referred to as the **sum of products**. When the sum of products is divided by $(n - 1)$, the resulting value represents a measure that is referred to as the **covariance**. Equation 28.39 is the computational equation for the covariance.

$$\text{cov}_{XY} = \frac{\sum XY - \frac{(\sum X)(\sum Y)}{n}}{n - 1} \quad (\text{Equation 28.39})$$

Equation 28.40 is the definitional equation of the covariance, which reveals the fact that covariance is an index of the degree to which two variables covary (i.e., vary in relation to one another).

$$\text{cov}_{XY} = \frac{\sum_{i=1}^n [(X_i - \bar{X})(Y_i - \bar{Y})]}{n - 1} \quad (\text{Equation 28.40})$$

Each subject's contribution to the covariance is computed as follows: The difference between a subject's score on the X variable and the mean of the X variable, and the difference between a subject's score on the Y variable and the mean of the Y variable are computed. The two resulting deviation scores are multiplied together. The resulting product represents that subject's contribution to the covariance. Upon obtaining a product for all n subjects, the sum of the n products (which is the numerator of Equation 28.1) is divided by $(n - 1)$. The resulting value represents the covariance, which it can be seen is essentially the average of the products of the deviation scores. The reason why the sum of the products is divided by $(n - 1)$ instead of n is because (as is also the case in computing the variance) division by the latter value provides a biased estimate of the population covariance. In the event one is computing a covariance for a sample and not using it as an estimate of the underlying population covariance, n is employed as the denominator of Equations 28.39 and 28.40.

Inspection of Equation 28.40 reveals that subjects who are above the mean on both variables or below the mean on both variables will contribute a positive product to the covariance. On the other hand, subjects who are above the mean on one of the variables but below the mean on the other variable will contribute a negative product to the covariance. If all or most of the subjects contribute positive products, the covariance will be a positive number. Since the value of r is a direct function of the sign of the covariance (which is a function of the sum of products), the resulting correlation coefficient will be a positive number. If all or most of the subjects contribute negative products, the covariance will be a negative number, and, consequently, the resulting correlation coefficient will also be negative. When among the n subjects the distribution of negative and positive products is such that they sum to zero, the sum of products will equal zero resulting in zero covariance, and r will equal zero. If, for one of the two variables, all subjects obtain the identical score, each subject will yield a product of zero, resulting in zero covariance (since the sum of products will equal zero). However, as noted in Section VI, since the value for the sum of squares will equal zero for a variable on which all subjects have the same score, Equation 28.1 becomes insoluble when all subjects have the same score on either of the variables. Based on what has been said with respect to the relationship between the sum of products and the covariance, the computation of r can be summarized by either of the following equations: $r = \text{cov}_{XY}/(\bar{s}_X \bar{s}_Y)$ and $r = SP_{XY}/\sqrt{SS_X SS_Y}$.

4. The homoscedasticity assumption of the Pearson product-moment correlation coefficient

It is noted in Section I that one of the assumptions underlying the **Pearson product-moment correlation coefficient** is a condition referred to as **homoscedasticity** (**homo** means same and **scedastic** means scatter). Homoscedasticity exists in a set of data if the relationship between the X and Y variables is of equal strength across the whole range of both variables. Data that are not homoscedastic are **heteroscedastic**. When data are homoscedastic the accuracy of a prediction based on the regression line will be consistent across the full range of both variables. To illustrate, if data are homoscedastic and a strong positive correlation is computed between X and Y , the strong positive correlation will exist across all values of both variables. However, if for high values of X the correlation between X and Y is a strong positive one, but the strength of this relationship decreases as the value of X decreases, the data are heteroscedastic. As a general rule, if the distribution of one or both of the variables employed in a correlation is saliently skewed, the data are likely to be heteroscedastic. When, however, the data for both variables are distributed normally, the data will be homoscedastic.

Figure 28.6 presents two regression lines (which it will be assumed represent the **regression line of Y on X**) and the accompanying data points. Note that in Figure 28.6a, which represents homoscedastic data, the distance of the data points from the regression line is about the same along the entire length of the line. Figure 28.6b, on the other hand, represents heteroscedastic data, since the data are not dispersed evenly along the regression line. Specifically, in Figure 28.6b the data points are close to the line for high values of X , yet as the value of X decreases, the data points become further removed from the line. Thus, the strength of the positive correlation is much greater for high values of X than it is for low values. This translates into the fact that a subject's Y score can be predicted with a greater degree of accuracy if the subject has a high score on the X variable as opposed to a low score. Directly related to this is the fact that the value of the standard error of estimate computed with Equation 28.12 ($s_{Y.X}$) will not be a representative measure of error variability for all values of X . Specifically, when $\tilde{s}_{Y.X}$ computed with Equation 28.14 (which is a function of the value $s_{Y.X}$) is employed to compute a confidence interval through use of Equation 28.16, the value of $\tilde{s}_{Y.X}$ will be larger for subjects who have a low score on the X variable, and thus the confidence interval associated with the predicted scores of such subjects will be larger than the confidence interval for subjects who have a high score on the X variable.

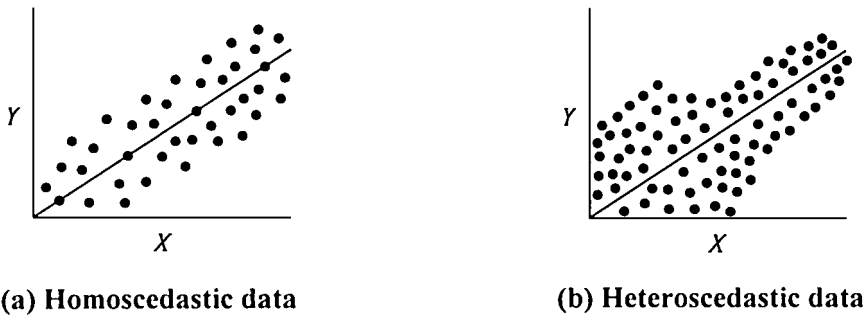


Figure 28.6 Homoscedastic Versus Heteroscedastic Data

5. The phi coefficient as a special case of the Pearson product-moment correlation coefficient A number of the correlational procedures discussed in this book represent special cases of the **Pearson product-moment correlation coefficient**. One of the procedures, the **phi coefficient**, is described in Section VI of the **chi-square test for $r \times c$ tables (Test 16)**. Another of the procedures, the **point-biserial correlation coefficient**, is described in Section IX (the **Addendum**). A third procedure, **Spearman's rank-order correlation coefficient**, is discussed in the next chapter.

In this section it will be demonstrated how the **phi coefficient (ϕ)** can be computed with Equation 28.1. In the discussion of the latter measure of association, it is noted that the value of **phi** is equivalent to the value of the **Pearson product-moment correlation coefficient** that will be obtained if the scores 0 and 1 are employed with reference to two dichotomous variables in a 2×2 contingency table. Using the data for Examples 16.1/16.2 (which employ a 2×2 contingency table), the scores 0 and 1 are employed for each of the categories on the two variables. Table 28.3 summarizes the data.

Table 28.3 reveals the following: 30 subjects have both an X score and a Y score of 0; 70 subjects have an X score of 1 and a Y score of 0; 60 subjects have an X score of 0 and a Y score of 1; 40 subjects have both an X score and a Y score of 1. Employing this information we can determine $\Sigma X = 110$, $\Sigma X^2 = 110$, $\Sigma Y = 100$, $\Sigma Y^2 = 100$, $\Sigma XY = 40$. Substituting these

Table 28.3 Summary of Data for Examples 16.1/16.2

		X variable		Row sums
		0	1	
Y variable	0	$a = 30$	$b = 70$	100
	1	$c = 60$	$d = 40$	100
Column sums		90	110	Total = 200

values in Equation 28.1, the value $r = .30$ is computed. The latter value is identical to $\phi = .30$ computed for Examples 16.1/16.2 with Equations 16.17 and 16.18.

$$r = \frac{40 - \frac{(110)(100)}{200}}{\sqrt{\left[110 - \frac{(110)^2}{200}\right]\left[100 - \frac{(100)^2}{200}\right]}} = .30$$

6. Autocorrelation/serial correlation In Section IX (the **Addendum**) of the **single-sample runs test (Test 10)** a number of procedures are discussed that are employed in determining whether the ordering of a series of numbers is random. Among the procedures that are briefly discussed is **autocorrelation**, which is also known as **serial correlation**. In contrast to most of the tests of randomness discussed in Section IX of the **single-sample runs test** (which can only be employed with a discrete variable) autocorrelation can be employed to evaluate either a continuous or discrete variable for randomness.

The most basic methodology that can be employed for autocorrelation is to pair each of the numbers in a series of n numbers with the number that follows it in the series. Upon doing this, the **Pearson product-moment correlation coefficient** between the resulting $(n - 1)$ pairs of numbers is computed. It is also possible to pair each number with the number whose ordinal position is some value other than one digit after it. In other words, each number can be paired with the number that is two digits after it, three digits after it, etc., or, with the number that is one, two, three, etc. digits before it in the series. In autocorrelation the number of digits that separate two values that are paired with one another is referred to as the **lag value**. In the example to be employed in this section the **lag +1** will be used, since each number will be paired with the number that is one ordinal position above it in the series. If, instead, each number is paired with the number that falls two ordinal positions above it in the series, the lag value is +2. If, on the other hand, each number is paired with the number that precedes it by one ordinal position in the series, the lag value is -1 . The higher the absolute value of the lag value, the fewer the number of pairs that will be employed in computing the correlation. Thus, if in a series of ten digits each number is paired with the number that is above it by two ordinal positions, there will only be $n - 2 = 8$ pairs of X and Y scores. This is the case, since the first two numbers in the series can only be X scores, and the last two numbers in the series can only be Y scores. Regardless of the lag value employed in an autocorrelation, if the sequence of numbers in a series is random, the computed value of the correlation coefficient should equal zero.

One variant of the methodology described in this section (which is referred to as **non-circular serial correlation**) is a procedure referred to as **circular serial correlation**. In circular serial correlation every number in a series of n numbers is paired with another number, including any numbers in the series that do not have a number following it. Numbers that are not followed by any numbers are sequentially paired with the numbers at the beginning of the series. Thus, if

the lag value is +1, the last number in the series is paired with the first number in the series. If the lag value is +2, the $(n - 1)^{th}$ number is paired with the first number in the series, and the n^{th} number is paired with the second number in the series.

To illustrate autocorrelation, the following ten digit series of numbers will be evaluated: 4, 3, 5, 2, 1, 3, 2, 1, 1, 2. In Table 28.4 the ten digits are arranged sequentially from top to bottom in Column A. The same ten digits are arranged sequentially in Column B, except for the fact that they are arranged so that each digit in Column B is adjacent to the digit in Column A that directly precedes it in the series. If each pair of adjacent values is treated as a set of scores, the value in Column A can be designated as an *X* score, and the value in Column B can be designated as a *Y* score. If the latter is done, each of the ten digits in the series will at some point be designated as both an *X* score and a *Y* score, except for the first digit which will only be an *X* score and the last digit which will only be a *Y* score.

Table 28.4 Arrangement of Numbers for Autocorrelation	
Column A	Column B
	4
4	3
3	5
5	2
2	1
1	3
3	2
2	1
1	1
1	2
2	

Table 28.5, which contains the nine pairs of digits in Table 28.4, summarizes the required values for computing the **Pearson product-moment correlation coefficient**. Note that the value $n = 9$ is employed in computing the value of r , since that is the number of sets of paired scores. Employing Equation 28.1, the value $r = .28$ is computed for the correlation coefficient.

$$r = \frac{53 - \frac{(22)(20)}{9}}{\sqrt{\left[70 - \frac{(22)^2}{9}\right]\left[58 - \frac{(20)^2}{9}\right]}} = .28$$

Table 28.5 Data for Autocorrelation					
<i>X</i>	<i>X</i> ²	<i>Y</i>	<i>Y</i> ²	<i>XY</i>	
4	16	3	9	12	
3	9	5	25	15	
5	25	2	4	10	
2	4	1	1	2	
1	1	3	9	3	
3	9	2	4	6	
2	4	1	1	2	
1	1	1	1	1	
1	1	2	4	2	
Σ <i>X</i> = 22	Σ <i>X</i> ² = 70	Σ <i>Y</i> = 20	Σ <i>Y</i> ² = 58	Σ <i>XY</i> = 53	

If the usual criteria for evaluating an r value are employed, the degrees of freedom for the analysis are $df = n - 2 = 9 - 2 = 7$. In **Table A16**, the tabled critical two-tailed .05 and .01 values for $df = 7$ that are employed to evaluate the nondirectional alternative hypothesis $H_1: \rho \neq 0$ are $r_{.05} = .666$ and $r_{.01} = .798$. Since the computed value $r = .28$ is less than $r_{.05} = .666$, the null hypothesis $H_0: \rho = 0$ cannot be rejected. Thus, the data do not indicate that the underlying population correlation is some value other than zero.

In point of fact, the tabled critical values in **Table A16** are not the most appropriate values for evaluating the value $r = .28$. This is the case, since the sampling distribution for a serial correlation coefficient is not identical to the sampling distribution upon which the values in **Table A16** are based. The sampling distribution upon which **Table A16** is based assumes that the n pairs of scores are independent of one another. Since in **Table 28.5** all of the digits in the series (with the exception of the last digit) represent both an X and a Y variable, the latter assumption is violated. Because the pairs are not independent, the residuals derived from the data may also not be independent (independence of the residuals is an underlying assumption of the least squares regression model).²¹ Although not necessarily the case with pseudorandom numbers (i.e., a series of random numbers generated with a computer algorithm), it is common in autocorrelated data in business and economics for residuals to be dependent on one another. Most commonly, in the latter disciplines there is a positive correlation between residuals. When the latter is true, residuals of the same sign occur in clusters — i.e., residuals for adjacent pairs have the identical sign. When there is a negative autocorrelation, adjacent residuals tend to alternate between a positive and negative sign.

Because of the fact that the residuals may not be independent, a sampling distribution other than the one upon which the critical values in **Table A16** are based should be employed to evaluate the value $r = .28$ computed with Equation 28.1. Anderson (1942) demonstrated that in the sampling distribution for a serial correlation, the absolute value of a critical value at a prespecified level of significance is smaller than the corresponding critical value in **Table A16**. Furthermore, the limits that define a critical value at a prespecified level of significance are asymmetrical (i.e., the absolute value of a critical value will not be identical for a positive versus a negative r value). Anderson (1942) computed the critical two-tailed .05 and .01 values of r for values of n between 5 and 75 for lag +1. For large sample sizes he determined that Equation 28.41 (which employs the normal distribution) can be used to provide a good approximation of the critical values of r when the lag value is +1.²²

$$r = \pm z \sqrt{\frac{n-2}{(n-1)^2} - \frac{1}{n-1}} \quad (\text{Equation 28.41})$$

Where: z represents the tabled critical value in the normal distribution that corresponds to the prespecified level of significance employed in evaluating r

n represents the total number of numbers in the series. Note that n is not the number of pairs of numbers employed in computing the coefficient of correlation.

Employing the values derived by Anderson (1942) for the exact sampling distribution of the serial correlation coefficient (which is not reproduced in this book), it can be determined (for $\alpha = .05$ and $n = 10$) that in order to reject the null hypothesis $H_0: \rho = 0$, the computed value of r must be equal to or greater than $r_{.05} = .360$ or equal to or less than $r_{.05} = -.564$. (The value of n used in Anderson's (1942) table represents the total number of digits in the series and not the number of pairs of digits employed in computing the correlation.) Since $r = .28$ is less than $r_{.05} = .360$, the null hypothesis can be retained. Thus, regardless of whether one employs **Table**

A16 or Anderson's (1942) critical values, the null hypothesis is retained. Nevertheless, the difference between the critical values in the two tables is substantial.

Use of Anderson's (1942) tables and/or Equation 28.41 provide for a more powerful test of the alternative hypothesis $H_0: \rho \neq 0$ than do the critical values in **Table A16**. Although the degree of discrepancy between a critical value in **Table A16** and a critical value computed with Equation 28.41 decreases as the size of n increases, even for large sample sizes the absolute values in **Table A16** are noticeably higher. It should be noted that use of Equation 28.41 with small samples yields absolute critical values that are too high.

It is noted in the discussion of tests of randomness under the **single-sample runs test**, that it is not uncommon for two or more of the available tests for determining randomness to yield conflicting results. Although autocorrelation is not considered to be among the most rigorous tests for randomness, if one conducts multiple autocorrelations on a series (i.e., for the lag values +1, +2, +3, etc. and -1, -2, -3, etc.), and all or most lead to retention of the null hypothesis, such a protocol will provide a more authoritative analysis with respect to randomness than will the single analysis for lag +1 conducted in this section. It should be noted that if for a series of n numbers (where the value of n is large) an autocorrelation is conducted for every possible positive and negative lag value, just by chance it is expected that some of the computed serial correlations will be significant. Whatever prespecified alpha value the researcher employs will determine the proportion of significant correlations that can be obtained which will still allow one to retain the null hypothesis $H_0: \rho = 0$.

One limitation of autocorrelation as a test of randomness should be noted. Assume that a researcher is evaluating a series in which in any trial a number can assume any one of $k = 5$ possible values. For instance, in the example employed in this section it is assumed that the integer values 1, 2, 3, 4, 5 are the only possible values that can occur. In a truly random series of reasonable length, each of the five digits would be expected to occur approximately the same number of times. Yet, it is entirely possible to have a series of numbers in which one or more of the integer values do not even occur one time, yet the resulting autocorrelation is $r = 0$. For instance, a computer can be programmed to generate a series of 1000 pseudorandom numbers employing the integer values 1, 2, 3, 4, 5. Yet it is theoretically possible for the computer algorithm to generate 1000 digits, all of which are either 1 or 2. If the autocorrelation between the values of 1 and 2 that are generated is zero, it will suggest the sequence of numbers is random. Although it may be a random sequence for a population in which the only values the numbers may assume are the integer values 1 or 2, it is not a random series for a population in which the numbers may assume an integer value between 1 and 5. Whereas most of the other tests that are employed in evaluating randomness will identify this problem, autocorrelation will not.

Autocorrelation and the derivation of the corresponding regression equations (referred to as **autoregression**) are complex subjects that are primarily discussed in books that deal with statistical applications in business and economics. Research in such fields as economics, business, and political science often employs autocorrelation for **time series analysis**, which is a methodology for studying the sequential progression of events. The results of a time series analysis can be useful in predicting future values for such variables as stock prices, sales revenues, crop yields, crime rates, weather, etc. Such predictions are predicated on the fact that significant data based on autocorrelation indicate sequential dependence with respect to the variable of interest. As is the case with Example 28.1, a regression equation that is derived from data that are autocorrelated is employed in making predictions. Use of a regression equation in this context is referred to as **autoregression**. Sources that discuss autoregression note that derivation of a regression equation through use of the method of least squares as described in Section VI will underestimate error variability and, consequently, will not provide the most accurate basis for prediction. For this reason when autocorrelation is employed with a set of data, alternative

procedures are recommended for making predictions, as well as for evaluating the null hypothesis $H_0: \rho = 0$. A procedure recommended in most sources is one developed by Durbin and Watson (1950, 1951, 1971). Among the sources that describe the **Durbin–Watson test** (which is only appropriate for a lag value of +1) are Chou (1989), Montgomery and Peck (1992), and Netter *et al.* (1983). The latter sources also describe other alternative approaches for autoregression. Other books that discuss autocorrelation are Schmidt and Taylor (1970) and Banks and Carson (1984).

VIII. Additional Examples Illustrating the Use of the Pearson Product-Moment Correlation Coefficient

Two additional examples that can be evaluated with the **Pearson product-moment correlation coefficient** are presented in this section. Since the data for Examples 28.2 and 28.3 are identical to the data employed in Example 28.1, they yield the same result.

Example 28.2 *The editor of an automotive magazine conducts a survey to see whether it is possible to predict the number of traffic citations one receives for speeding based on how often a person changes his or her motor oil. The responses of five subjects on the two variables follow. (For each subject, the first score represents the number of oil changes (which represents the X variable), and the second score the number of traffic citations (which represents the Y variable).) Subject 1 (20, 7); Subject 2 (0, 0); Subject 3 (1, 2); Subject 4 (12, 5); Subject 5 (3, 3). Do the data indicate there is a significant correlation between the two variables?*

Example 28.3 *A pediatrician speculates that the length of time an infant is breast fed may be related to how often a child becomes ill. In order to answer the question, the pediatrician obtains the following two scores for five three-year-old children: The number of months the child was breast fed (which represents the X variable) and the number of times the child was brought to the pediatrician's office during the current year (which represents the Y variable). The scores for the five children follow: Child 1 (20, 7); Child 2 (0, 0); Child 3 (1, 2); Child 4 (12, 5); Child 5 (3, 3). Do the data indicate that the length of time a child is breast fed is related to the number of times a child is brought to the pediatrician?*

IX. Addendum

The **Addendum** will discuss four additional topics that are directly or indirectly related to the general subject of correlational analysis.

1) The first part of the **Addendum** describes three bivariate correlational measures that are related to the **Pearson product-moment correlation coefficient**. The three procedures that will be described are a) The **point-biserial correlation coefficient (Test 28h)**; b) The **biserial correlation coefficient (Test 28i)**; and c) The **tetrachoric correlation coefficient (Test 28j)**.

2) The second part of the **Addendum** describes the following **multivariate correlational** measures that are employed within the framework of **multiple regression analysis**: a) The **multiple correlation coefficient (Test 28k)**; b) The **partial correlation coefficient (Test 28l)**; and c) The **semi-partial correlation coefficient (Test 28m)**. The use of the term multivariate within the framework of the procedures to be described in this section implies that data for three or more variables are employed in the analysis.

3) The third part of the **Addendum** provides a general overview of the following **multivariate statistical procedures**, which directly or indirectly involve some form of correlational analysis: a) **Factor analysis**; b) **Canonical correlation**; and c) **Discriminant analysis and**

logistic regression. The presentation of the material in this section will be nonmathematical, and except for factor analysis (which will be described in greater detail), the description of each procedure will be brief.

4) The fourth part of the **Addendum** discusses **meta-analysis and related topics**. **Meta-analysis** is methodology for pooling the results of multiple studies which evaluate the same general hypothesis. A major component of meta-analysis involves evaluating measures of **effect size**, which are correlational measures. Within the framework of the discussion of meta-analysis, criticisms that have been directed at the conventional hypothesis testing model will be considered. Specifically, the conventional hypothesis testing model employs the concept of statistical significance (as opposed to employing measures of effect size) as the criterion for defining the relationship between two or more variables in an experiment. Critics of the latter model argue that measures of effect size are more meaningful indicators than statistical significance of the nature and strength of the relationship between experimental variables.

1. Bivariate measures of correlation that are related to the Pearson-product moment correlation coefficient This section of the **Addendum** will describe three bivariate correlational measures that are related to the **Pearson product-moment correlation coefficient**. Each of the correlation coefficients to be described assumes that the scores on at least one of the variables can be expressed within the format of interval/ratio data, and that the underlying distribution of these scores is continuous and normal. Two of the correlational procedures assume that the underlying interval/ratio scores on one or both of the variables have been converted into a dichotomous (two category) format. A brief description of the three procedures follows:

The point-biserial correlation coefficient (Test 28h) The **point-biserial correlation coefficient** (r_{pb}) (which is a special case of the **Pearson product-moment correlation coefficient**) is employed if one variable is expressed as interval/ratio data, and the other variable is represented by a dichotomous nominal/categorical scale (i.e., two categories).

The biserial correlation coefficient (Test 28i) The **biserial correlation coefficient** (r_b) is employed if both variables are based on an interval/ratio scale, but the scores on one of the variables have been transformed into a dichotomous nominal/categorical scale. It provides an estimate of the value that would be obtained for the **Pearson product-moment correlation coefficient** if, instead of the dichotomized variable, one employed the scores on the underlying interval/ratio scale which the latter variable represents.

The tetrachoric correlation coefficient (Test 28j) The **tetrachoric correlation coefficient** (r_{tet}) is employed if both variables are based on an interval/ratio scale, but the scores on both of the variables have been transformed into a dichotomous nominal/categorical scale. It provides an estimate of the value that would be obtained for the **Pearson product-moment correlation coefficient**, if, instead of the dichotomized variables, one employed the scores on the underlying interval/ratio scales that the latter variables represent.

Test 28h: The point-biserial correlation coefficient (r_{pb}) As noted earlier, the **point-biserial correlation coefficient** represents a special case of the **Pearson product-moment correlation coefficient**. The **point-biserial correlation coefficient** is employed if one variable is expressed as interval/ratio data, and the other variable is represented by a dichotomous nominal/categorical scale. Examples of variables that constitute a dichotomous nominal/categorical scale are **male** versus **female** and **employed** versus **unemployed**. In using the **point-biserial correlation coefficient**, it is assumed that the dichotomous variable is not based on an underlying continuous interval/ratio distribution. If, in fact, the dichotomous variable is based on the latter type of distribution, the **biserial correlation coefficient (Test 28i)** is the appropriate measure to employ. Examples of variables that are expressed in a dichotomous format, but which are based on an

underlying continuous interval/ratio distribution are **pass** versus **fail** and **above average intelligence** versus **below average intelligence**. Obviously, not everyone who passes (or fails) a test or a course performs at the same level. In the same respect, the distribution of intelligence of people who are **above average** or **below average** is not uniform. There are, of course, variables with respect to which it can be argued whether they are based on an underlying continuous distribution (such as perhaps handedness, which will be employed as a dichotomous variable in the example to be presented in this section). As is the case with the **Pearson product-moment correlation coefficient**, the range of values within which r_{pb} can fall are $-1 \leq r_{pb} \leq +1$. Example 28.4 will be employed to illustrate the use of the **point-biserial correlation coefficient**.

Example 28.4 *A study is conducted to determine whether there is a correlation between handedness and eye-hand coordination. Five right-handed and five left-handed subjects are administered a test of eye-hand coordination. The test scores of the subjects follow (the higher a subject's score, the better his or her eye-hand coordination): **Right-handers:** 11, 1, 0, 2, 0; **Left-handers:** 11, 11, 5, 8, 4. Is there a statistical relationship between handedness and eye-hand coordination?*

In the analysis handedness will represent the X variable, and the eye-hand coordination test scores will represent the Y variable. With respect to handedness (which is a dichotomous variable), all right-handed subjects will be assigned a score of 1 on the X variable, and all left-handed subjects will be assigned a score of 0. Table 28.6 summarizes the data for the ten subjects employed in the study.

Table 28.6 Data for Example 28.4

Subject	X	X^2	Y	Y^2	XY
1	1	1	11	121	11
2	1	1	1	1	1
3	1	1	0	0	0
4	1	1	2	4	2
5	1	1	0	0	0
6	0	0	11	121	0
7	0	0	11	121	0
8	0	0	5	25	0
9	0	0	8	64	0
10	0	0	4	16	0
<hr/>					
	$\Sigma X = 5$	$\Sigma X^2 = 5$	$\Sigma Y = 53$	$\Sigma Y^2 = 473$	$\Sigma XY = 14$

Since the **point-biserial correlation coefficient** is a special case of the **Pearson product-moment correlation coefficient**, Equation 28.42 (which is identical to Equation 28.1) is employed to compute r_{pb} . Employing Equation 28.42, the value $r_{pb} = -.57$ is computed.

(Equation 28.42)

$$r_{pb} = \frac{\Sigma XY - \frac{(\Sigma X)(\Sigma Y)}{n}}{\sqrt{\left[\Sigma X^2 - \frac{(\Sigma X)^2}{n}\right]\left[\Sigma Y^2 - \frac{(\Sigma Y)^2}{n}\right]}} = \frac{14 - \frac{(5)(53)}{10}}{\sqrt{\left[5 - \frac{(5)^2}{10}\right]\left[473 - \frac{(53)^2}{10}\right]}} = -.57$$

Equation 28.43 is an alternative equation for computing the **point-biserial correlation coefficient**.

$$r_{pb} = \frac{\bar{Y}_1 - \bar{Y}_0}{\hat{s}_Y} \sqrt{p_0 p_1} \sqrt{\frac{n}{n-1}}$$

(Equation 28.43)

$$= \frac{2.8 - 7.8}{4.62} \sqrt{(.5)(.5)} \sqrt{\frac{10}{10-1}} = -.57$$

Where: \bar{Y}_0 and \bar{Y}_1 are, respectively, the average scores on the Y variable for subjects who are categorized 0 versus 1 on the X variable
 p_0 equals the proportion of subjects with an X score of 0
 p_1 equals the proportion of subjects with an X score of 1

In employing Equation 28.43, $\bar{Y}_1 = 2.8$ and $\bar{Y}_0 = 7.8$. The value $\hat{s}_Y = 4.62$, which represents the unbiased estimate of the population standard deviation for the Y variable (which is computed with Equation I.8), is computed below.

$$\hat{s}_Y = \sqrt{\frac{\sum Y^2 - \frac{(\sum Y)^2}{n}}{n-1}} = \sqrt{\frac{473 - \frac{(53)^2}{10}}{10-1}} = 4.62$$

It should be noted that some sources employ Equation 28.44 to compute the value of the **point-biserial correlation coefficient**.

$$r_{pb} = \frac{\bar{Y}_1 - \bar{Y}_0}{s_Y} \sqrt{p_0 p_1} = \frac{2.8 - 7.8}{4.38} \sqrt{(.5)(.5)} = -.57 \quad \text{(Equation 28.44)}$$

Note that Equation 28.44 employs the sample standard deviation (computed with Equation I.7 — i.e., $s_Y = \sqrt{[\sum Y^2 - ((\sum Y)^2/n)]/n}$), which is a biased estimate of the population standard deviation. For Example 28.2, $s_Y = 4.38$. When $s_Y = 4.38$ is substituted in the Equation 28.44, it yields the value $r_{pb} = -.57$.

The reader should take note of the fact that the sign of r_{pb} is irrelevant unless the categories on the dichotomized variable are ordered (which is not the case for Example 28.4). The reason for employing the absolute value of r_{pb} is that the use of the scores 0 and 1 for the two categories is arbitrary, and does not indicate that one category is superior to the other. (If all right-handed subjects are assigned a score of 0 on the X variable and all left-handed subjects are assigned a score of 1, the value computed for $r_{pb} = +.57$, which is the same absolute value computed for the data in Table 28.6.) Since the categories are not ordered, from this point on in the discussion, the absolute value $r_{pb} = .57$ will be employed to represent the value of r_{pb} . In the event the categories are ordered, the score 1 should be employed for the category associated with higher performance/quality, and the score 0 should be employed for the category associated with lower performance/quality. In all likelihood, if the categories are ordered they are likely to be based on an underlying continuous distribution, and in such a case the appropriate correlational measure to employ is the **biserial correlation coefficient**.

The square of the **point-biserial correlation coefficient** represents the **coefficient of**

determination, which as noted in Section VI indicates the amount of variability on the Y variable that can be accounted for by variability on the X variable. Since, $r_{pb}^2 = (.57)^2 = .325$, 32.5% of the variability on the test of eye-hand coordination can be accounted for on the basis of a person's handedness.

The data employed for Example 28.4 are identical to that employed for Example 11.1 (which is used to illustrate the **t test for two independent samples**). In point of fact, the **point-biserial correlation coefficient** can be employed to measure the magnitude of treatment effect in an experiment that has been evaluated with a **t test for two independent samples**, if the grouping of the subjects is conceptualized as the dichotomous variable. Thus, in Example 11.1, if each subject in Group 1 (Drug Group) is assigned an X score of 1, and each subject in Group 2 (Placebo Group) is assigned an X score of 0, the data for the experiment can be summarized with Table 28.6. Since analysis of the data in Table 28.6 yields $r_{pb} = .57$ and $r_{pb}^2 = .325$, the researcher can conclude that 32.5% of the variability on the dependent variable (the depression ratings for subjects) can be accounted for on the basis of which group a subject is a member.

In Section VI of the **t test for two independent samples**, the measure of association that is employed to measure the magnitude of treatment effect is the **omega squared** ($\tilde{\omega}^2$) statistic. The value of **omega squared** computed for Example 11.1 is $\tilde{\omega}^2 = .22$. Since $\tilde{\omega}^2$ is interpreted in the same manner as r_{pb}^2 , the value $\tilde{\omega}^2 = .22$ indicates that 22% of the variability on the dependent variable can be accounted for on the basis of which group a subject is a member. Obviously, the latter value is lower than the value $r_{pb}^2 = .325$ computed in this section. The discrepancy between the two values will be discussed further later in this section. In point of fact, $r_{pb}^2 = .325$ is equivalent to the **eta squared** ($\tilde{\eta}^2$) statistic, which is an alternative measure of association that some sources employ in assessing the magnitude of treatment effect for the **t test for two independent samples**. Marascuilo and Serlin (1988) note that both r_{pb}^2 and $\tilde{\eta}^2$ represent a **correlation ratio**. The **correlation ratio**, which can be defined within the framework of an analysis of variance, is the ratio of the explained sum of squares over the total sum of squares. To clarify the meaning of a correlation ratio, let us assume that in lieu of the **t test for two independent samples**, the data for Example 11.1 are evaluated with the **single-factor between-subjects analysis of variance (Test 21)**. Table 28.7 is the summary table of the analysis of variance for Example 11.1.

Table 28.7 Summary Table of Analysis of Variance for Example 11.1

Source of variation	SS	df	MS	F
Between-groups	62.5	1	62.5	3.86
Within-groups	129.6	8	16.2	
Total	192.1	9		

Within the framework of the **single-factor between-subjects analysis of variance**, the **correlation ratio** (which is computed with Equation 21.43) is $\tilde{\eta}^2 = SS_{BG}/SS_T$. Since both $\tilde{\eta}^2$ and r_{pb}^2 represent the correlation ratio, $\tilde{\eta}^2 = r_{pb}^2 = SS_{BG}/SS_T$. Thus, for Example 11.1, $\tilde{\eta}^2 = r_{pb}^2 = 62.5/192.1 = .325$.

Equation 28.45 can also be employed to compute the value $\tilde{\eta}^2 = r_{pb}^2$ (where $t = \sqrt{F} = \sqrt{3.86} = 1.964$).

$$\tilde{\eta}^2 = r_{pb}^2 = \frac{t^2}{t^2 + df} = \frac{(1.964)^2}{(1.964)^2 + 8} = .325 \quad (\text{Equation 28.45})$$

Where: $df = n_1 + n_2 - 2$ (which is the degrees of freedom for the t test for two independent samples)

The fact that different measures of magnitude of treatment effect may not yield the same value is discussed in Section VI of the **single-factor between-subjects analysis of variance**. In the latter discussion it is noted that the computed value $\hat{\eta}^2$ is a biased estimate of the underlying population parameter η^2 , and an adjusted value (which is less biased) can be computed with Equation 21.44. The latter value is now computed for Example 11.1: Adjusted $\hat{\eta}^2 = 1 - [MS_{WG}/MS_T] = 1 - [16.2/21.34] = .24$. (Where, $MS_T = SS_T/df_T = 192.1/9 = 21.34$.) Note that the value Adjusted $\hat{\eta}^2 = .24$ is closer to the value $\hat{\omega}^2 = .22$ than the previously computed value $\hat{\eta}^2 = r_{pb}^2 = .325$.

Test 28h-a: Test of significance for a point-biserial correlation coefficient The null hypothesis $H_0: \rho_{pb} = 0$ can be evaluated with Equation 28.46 (which is identical to Equation 28.3, which is employed to evaluate the same hypothesis with reference to the **Pearson product-moment correlation coefficient**). As is the case for Equation 28.3, the degrees of freedom for Equation 28.46 are $df = n - 2$. Employing Equation 28.46, the value $t = 1.96$ is computed.

$$t = \frac{r_{pb}\sqrt{n-2}}{\sqrt{1-r_{pb}^2}} = \frac{.57\sqrt{10-2}}{\sqrt{1-(.57)^2}} = 1.96 \quad (\text{Equation 28.46})$$

It will be assumed that the nondirectional alternative hypothesis $H_1: \rho_{pb} \neq 0$ is evaluated. Employing **Table A2**, for $df = 10 - 2 = 8$, the tabled critical two-tailed .05 and .01 values are $t_{.05} = 2.31$ and $t_{.01} = 3.36$. Since the obtained value $t = 1.96$ is less than both of the aforementioned critical values, the null hypothesis $H_0: \rho_{pb} = 0$ cannot be rejected.

Since the value of the **point-biserial correlation coefficient** is a direct function of the difference between \bar{Y}_0 and \bar{Y}_1 , a significant difference between the latter two mean values indicates that the absolute value of the correlation between the two variables is significantly above zero. Thus, an alternative way of evaluating the null hypothesis $H_0: \rho_{pb} = 0$ is to conduct a **t test for two independent samples**, contrasting the two mean values \bar{Y}_0 and \bar{Y}_1 . The fact that the latter analysis will yield a result that is equivalent to that obtained with Equation 28.46 can be confirmed by the fact that the value $t = 1.96$ computed above with Equation 28.46 is identical to the absolute t value computed for the same set of data with Equation 11.1 (for Example 11.1). Sources that provide additional discussion of the **point-biserial correlation coefficient** are Guilford (1965), Lindeman *et al.* (1980), and McNemar (1969).

Test 28i: The biserial correlation coefficient (r_b) The **biserial correlation coefficient** is employed if both variables are based on an interval/ratio scale, but the scores on one of the variables have been transformed into a dichotomous nominal/categorical scale. An example of a situation where an interval/ratio variable would be expressed as a dichotomous variable is a test based on a normally distributed interval/ratio scale for which the only information available is whether a subject has passed or failed the test. The value computed for the **biserial correlation coefficient** represents an estimate of the value that would be obtained for the **Pearson product-moment correlation coefficient**, if, instead of employing a dichotomized variable, one had employed the scores on the underlying interval/ratio scale.

The **biserial correlation coefficient** is based on the assumption that the underlying distribution for both of the variables is continuous and normal. Since the accuracy of r_b is highly dependent upon the assumption of normality, it should not be employed unless there is empirical

evidence to indicate that the distribution underlying the dichotomous variable is normal. If the underlying distribution of the dichotomous variable deviates substantially from normality, the computed value of r_b will not be an accurate approximation of the underlying population correlation r_b estimates. One consequence of the normality assumption being violated is that, under certain conditions, the absolute value computed for r_b may exceed 1. In point of fact, Lindeman *et al.* (1980) note that the theoretical limits of r_b are $-\infty \leq r_b \leq +\infty$.

In contrast to r_{pb} , the sign of the **biserial correlation coefficient** should be taken into account, since it clarifies the nature of the relationship between the two variables. This is the case, since the dichotomous variable will involve two ordered categories. In assigning scores to subjects on the ordered dichotomized variable, the score 1 should be employed for the category associated with higher performance/quality, and the score 0 should be employed for the category associated with lower performance/quality.

In order to illustrate the computation of the **biserial correlation coefficient**, let us assume a researcher wants to determine whether there is a statistical relationship between intelligence and eye-hand coordination. Ten subjects are categorized with respect to both variables. Although the evaluation of each subject's intelligence is based on an interval/ratio intelligence test score, we will assume that the only information available to the researcher is whether an individual is above or below average in intelligence. In view of this, intelligence, which will be designated the X variable, will have to be represented as a dichotomous variable. Subjects who are above average in intelligence will be assigned a score of 1, and subjects who are below average in intelligence will be assigned a score of 0. The scores on the eye-hand coordination test will represent the Y variable. Example 28.5, which employs the same set of data as Example 28.4, summarizes the above described experiment.

Example 28.5 *A study is conducted to determine whether there is a correlation between intelligence and eye-hand coordination. Five subjects who are above average in intelligence and five subjects who are below average in intelligence are administered a test of eye-hand coordination. The test scores of the subjects follow (the higher a subject's score, the better his or her eye-hand coordination): Above average intelligence: 11, 1, 0, 2, 0; Below average intelligence: 11, 11, 5, 8, 4. Is there a statistical relationship between intelligence and eye-hand coordination?*

The **biserial correlation coefficient** can be computed with either Equation 28.47 or 28.48. It can also be computed with Equation 28.49 if r_{pb} has been computed for same set of data. Note that except for h , all of the terms in the aforementioned equations are also employed in computing the **point-biserial correlation coefficient**. The value h represents the height (known more formally as the **ordinate**) of the standard normal distribution at the point which divides the proportions p_0 and p_1 . Specifically, employing [Table A1](#) the z value is identified that delineates the point on the normal curve that a proportion of the cases corresponding to the smaller of the two proportions p_0 versus p_1 falls above and the larger of the two proportions falls below. The tabled value of h (in [Column 4](#) of [Table A1](#)) associated with that z value is employed in whatever equation one employs for computing r_b . If, as is the case in our example, $p_0 = p_1 = .5$, the value of z will equal zero, and thus the corresponding value of $h = .3989$. When $h = .3989$ and the other appropriate values employed for Example 28.5 (which are summarized in [Table 28.6](#)) are substituted in Equations 28.47–28.49, the value $r_b = -.71$ is computed.

(Equation 28.47)

$$r_b = \left[\frac{\bar{Y}_1 - \bar{Y}_0}{\tilde{s}_Y} \right] \left[\frac{p_0 p_1}{h} \right] \sqrt{\frac{n}{n-1}} = \left[\frac{2.8 - 7.8}{4.62} \right] \left[\frac{(.5)(.5)}{.3989} \right] \sqrt{\frac{10}{10-1}} = -.71$$

$$r_b = \left[\frac{\bar{Y}_1 - \bar{Y}_0}{s_Y} \right] \left[\frac{p_0 p_1}{h} \right] = \left[\frac{2.8 - 7.8}{4.38} \right] \left[\frac{(.5)(.5)}{.3989} \right] = -.71 \quad (\text{Equation 28.48})$$

$$r_b = \frac{r_{pb} \sqrt{p_0 p_1}}{h} = \frac{(-.57) \sqrt{(.5)(.5)}}{.3989} = -.71 \quad (\text{Equation 28.49})$$

Note that for the same set of data, the absolute value $r_b = .71$ is larger than the absolute value $r_{pb} = .57$ computed for the **point-biserial correlation coefficient**. In point of fact, for the same set of data (except when $r_b = r_{pb} = 0$) the absolute value of r_b will always be larger than the absolute value of r_{pb} , since $\sqrt{p_0 p_1}/h$ will always be larger than 1. The closer together the values p_0 and p_1 , the less the discrepancy between the values of r_b and r_{pb} . If there is reason to believe that the normality assumption for the dichotomous variable has been violated, most sources recommend computing r_{pb} instead of r_b , since r_b may be a spuriously inflated estimate of the underlying population correlation. When the latter is taken into consideration, along with the fact that by dichotomizing a continuous variable one sacrifices valuable information, it can be understood why the **biserial correlation coefficient** is infrequently employed within the framework of research.

Guilford (1965) notes that, given the normality assumption has not been violated, those conditions which optimize the likelihood of r_b providing a good estimate of the underlying population parameter ρ_b are as follows: a) The value of n is large; and b) The values of p_0 and p_1 are close together. It should be noted that (as is the case for Pearson r and r_{pb}) if the relationship between two variables is nonlinear, the computed value of r_b will only represent the degree of linear relationship between the variables.

Test 28i-a: Test of significance for a biserial correlation coefficient Lindeman *et al.* (1980) note that the null hypothesis $H_0: \rho_b = 0$ can be evaluated with Equation 28.50. Although the latter equation, which is based on the normal distribution, assumes a large sample size, it is employed to evaluate the value $r_b = -.71$ computed for Example 28.5. Note that the sign of z will always be the same as the sign of r_b .

$$z = \frac{hr_b}{\sqrt{\frac{p_0 p_1}{n}}} = \frac{(.3989)(-.71)}{\sqrt{\frac{(.5)(.5)}{10}}} = -1.79 \quad (\text{Equation 28.50})$$

Employing **Table A1**, the tabled critical two-tailed values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed values are $z_{.05} = 1.65$ and $z_{.01} = 2.33$. The nondirectional alternative hypothesis $H_1: \rho_b \neq 0$ is not supported, since the absolute value $z = 1.79$ is less than the tabled critical two-tailed value $z_{.05} = 1.96$. However, the directional alternative hypothesis $H_1: \rho_b < 0$ is supported at the .05 level, since $z = -1.79$ is a negative number with an absolute value that is greater than the tabled critical one-tailed value $z_{.05} = 1.65$. The moderately strong negative correlation between the two variables indicates that subjects who score below average

on the intelligence test perform better on the test of eye-hand coordination than do subjects who score above average on the intelligence test. The latter can be confirmed by the fact that $\bar{Y}_1 = 2.8$ is less than $\bar{Y}_0 = 7.8$.²³

As is the case for the **point-biserial correlation coefficient**, since the value of the **biserial correlation coefficient** is a direct function of the difference between \bar{Y}_0 and \bar{Y}_1 , a significant difference between the two mean values indicates that the absolute value of the correlation between the two variables is significantly above zero. Thus, an alternative way of evaluating the null hypothesis $H_0: \rho_b = 0$ is to contrast the means \bar{Y}_0 and \bar{Y}_1 with a ***t* test for two independent samples**. However, the result obtained with Equation 28.50 will not necessarily be consistent with the result obtained if the ***t* test for two independent samples** is employed to contrast \bar{Y}_0 versus \bar{Y}_1 (especially if the sample size is small). In point of fact, use of the ***t* test for two independent samples** to contrast \bar{Y}_0 versus \bar{Y}_1 assumes the use of r_{pb} as a measure of association. Within the context of employing the ***t* test**, the correlational example under discussion can be conceptualized as a study in which intelligence represents the independent variable and eye-hand coordination the dependent variable. The independent variable, which is nonmanipulated, is comprised of the two levels, **above average intelligence** versus **below average intelligence**. Sources that provide additional discussion of the **biserial correlation coefficient** are Guilford (1965), Lindeman *et al.* (1980), and McNemar (1969).

Test 28j: The tetrachoric correlation coefficient (r_{tet}) The **tetrachoric correlation coefficient** is employed if both variables are based on an interval/ratio scale, but the scores on both of the variables have been transformed into a dichotomous nominal/categorical scale. The value computed for the **tetrachoric correlation coefficient** represents an estimate of the value one would obtain for the **Pearson product-moment correlation coefficient** if, instead of employing dichotomized variables, one had used the scores on the underlying interval/ratio scales. The **tetrachoric correlation coefficient** (which was developed by Karl Pearson (1901)) is based on the assumption that the underlying distribution for both of the variables is continuous and normal. Among others, Cohen and Cohen (1983) note that caution should be employed in using both the **tetrachoric** and **biserial correlation coefficients**, since both measures are based on hypothetical underlying distributions that are not directly observed. Since the accuracy of r_{tet} is highly dependent upon the assumption of normality, it should not be employed unless there is empirical evidence to indicate that the distributions underlying the dichotomous variables are normal.

Since the magnitude of the standard error of estimate of r_{tet} is large relative to the standard error of estimate of Pearson r , in order to provide a reasonable estimate of r , the sample size employed for computing r_{tet} should be quite large. Guilford (1965) and Lindeman *et al.* (1980) state that the value of n employed in computing r_{tet} should be at least two times that which would be employed to compute r . As is the case for the **Pearson product-moment correlation coefficient**, the following apply to the **tetrachoric correlation coefficient**: a) The range of values within which r_{tet} can fall is $-1 \leq r_{tet} \leq +1$; and b) If the relationship between two variables is nonlinear, the computed value of r_{tet} will only represent the degree of linear relationship between the variables.

Earlier in this section (as well as in the discussion of the **chi-square test for $r \times c$ tables**) it is noted that the **phi coefficient** (ϕ) is also employed as a measure of association for a 2×2 contingency table involving two dichotomous variables. The basic difference between r_{tet} and ϕ , is that the latter measure is employed with two genuinely dichotomous variables (i.e., variables that are not based on an underlying distribution involving an interval/ratio scale). Cohen and Cohen (1983) and McNemar (1969) note that the value of r_{tet} computed for a 2×2 contingency table will always be larger than the value of ϕ computed for the same data.²⁴

A number of reasons account for the fact that the **tetrachoric correlation coefficient** is

infrequently employed within the framework of research. One reason is that, in most instances, data on variables that represent an interval/ratio scale are available in the latter format, and thus there is no need to convert it into a dichotomous format. Another reason is the reluctance of researchers to accept the normality assumption with respect to variables for which only dichotomous information is available.

Without the aid of a computer or special tables (which can be found in Guilford (1965) and Lindeman *et al.* (1980)), the computation of the exact value of r_{tet} is both time consuming and tedious. There are, however, two equations that have been developed which provide reasonably good approximations of r_{tet} under most conditions. These equations will be employed to evaluate Example 28.6.

Example 28.6 Two hundred subjects are asked whether they **Agree** (which will be assigned a score of 1) or **Disagree** (which will be assigned a score of 0) with the following two statements: **Question 1:** *I believe that abortion should be legal.* **Question 2:** *I believe that murderers should be executed.* The responses of the 200 subjects are summarized in Table 28.8. Is there a statistical relationship between subjects' responses to the two questions?

Table 28.8 Summary of Data for Example 28.6

		X variable Question 1		Row Sums
		0 Disagree	1 Agree	
Y variable Question 2	0 Disagree	$a = 30$	$b = 70$	100
	1 Agree	$c = 60$	$d = 40$	100
Column Sums		90	110	Total = 200

Subjects' responses to Question 1 will represent the X variable, and their responses to Question 2 will represent the Y variable. The use of the **tetrachoric correlation coefficient** in evaluating the data is based on the assumption that the permissible responses **Agree** versus **Disagree** represent two points that lie on a continuous scale. It will be assumed that if subjects are allowed to present their opinions to the questions with more precision, their responses can be quantified on an interval/ratio scale, and that the overall distribution of these responses in the underlying population will be normal. Thus, the responses of 0 and 1 on each variable are the result of dichotomizing information that is based on an underlying interval/ratio scale.

Equations 28.51 and 28.52 can be employed to compute reasonably good approximations of the value of r_{tet} . Lindeman *et al.* (1980) note that Equation 28.51 provides a good approximation of r_{tet} when $p_0 = p_1 = .5$ for both of the dichotomous variables. In other words, for the X variable both $p_{0_x} = (a + c)/n$ and $p_{1_x} = (b + d)/n$ will equal .5, and for the Y variable both $p_{0_y} = (a + b)/n$ and $p_{1_y} = (c + d)/n$ will equal .5 (where $n = a + b + c + d$). Equation 28.52, on the other hand, is recommended when the values of p_0 and p_1 are not equal. As the discrepancy between p_0 and p_1 increases, the less accurate the approximation provided by Equation 28.52 becomes.

In both Equations 28.51 and 28.52, a and d will always represent the frequencies of cells in which subjects provide the same response for both variables/questions, and b and c will always represent the frequencies of cells in which subjects provide opposite responses for the two variables/questions. Inspection of Table 28.8 (which is identical to Table 28.3, which is

employed to illustrate that ϕ is a special case of r) indicates the following: 1) $a = 30$ subjects respond **Disagree** to both questions; 2) $d = 40$ subjects respond **Agree** to both questions; 3) $b = 70$ subjects respond **Agree** to Question 1 and **Disagree** to Question 2; and 4) $c = 60$ subjects respond **Disagree** to Question 1 and **Agree** to Question 2.

The configuration of the data is such that $p_0 = p_1$ for the Y variable, and the relationship is closely approximated for the X variable. Specifically, for the Y variable, $p_{0_Y} = (a + b)/n = (30 + 70)/200 = .5$ and $p_{1_Y} = (c + d)/n = (60 + 40)/200 = .5$. In the case of the X variable, $p_{0_X} = (a + c)/n = (30 + 60)/200 = .45$ and $p_{1_X} = (b + d)/n = (70 + 40)/200 = .55$.

The appropriate values are substituted in Equations 28.51 and 28.52 below. The trigonometric functions in each of the equations can be easily calculated with one keystroke on most scientific calculators.

(Equation 28.51)

$$r_{\text{tet}} = \sin \left[90^\circ \left(\frac{a + d - b - c}{n} \right) \right] = \sin \left[90^\circ \left(\frac{30 + 40 - 70 - 60}{200} \right) \right] = \sin -27^\circ = -.45$$

(Equation 28.52)

$$r_{\text{tet}} = \cos \left(\frac{180^\circ}{1 + \sqrt{\frac{ad}{bc}}} \right) = \cos \left(\frac{180^\circ}{1 + \sqrt{\frac{(30)(40)}{(70)(60)}}} \right) = \cos 117.30^\circ = -.46$$

Since for both variables the condition $p_0 = p_1 = .5$ is present or approximated, the two equations result in almost identical values. The negative sign in front of the correlation coefficient reflects the fact that subjects who are in one response category on one variable are more likely to be in the other response category on the other variable. A positive correlation would indicate that subjects tend to be in the same response category on both variables. Note that the absolute value $r_{\text{tet}} = .45$ (or .46) is greater than the value $\phi = .30$ obtained for the same set of data. This is consistent with what was noted earlier — that the value of r_{tet} computed for a 2×2 table will always be larger than the value of ϕ computed for the same data. The reader should take note of the fact, however, that unlike r_{tet} , ϕ is always expressed as a positive number. Thus, in comparing the two values for the same set of data, the absolute value of r_{tet} should be employed.

Test 28j-a: Test of significance for a tetrachoric correlation coefficient In order to evaluate the null hypothesis $H_0: \rho_{\text{tet}} = 0$, the standard error of estimate of r_{tet} must first be computed employing Equation 28.53. In the latter equation, the values h_X and h_Y are the height (ordinate) of the standard normal distribution at the point for each of the variables which divides the proportions p_0 and p_1 . The protocol for determining the ordinate for each of the variables is identical to that employed for determining the ordinate for the **biserial correlation coefficient**. Employing **Table A1** for both the X and the Y variables, the z value is identified which delineates the point on the normal curve that a proportion of cases corresponding to the smaller of the two proportions p_0 versus p_1 falls above and the larger of the two proportions falls below. The corresponding ordinate (in **Column 4** of **Table A1**) is then determined. Thus, in the case of the X variable, $h_X = .3958$ (since 45% of cases fall above the corresponding value $z = .128$). (The value $h_X = .3958$ is interpolated from **Table A1**.) In the case of the Y variable, $h_Y = .3989$ (since 50% of cases fall above the corresponding value $z = 0$). When the appropriate values are substituted in Equation 28.53, the value $s_{r_{\text{tet}}} .111$ is computed.

$$s_{r_{\text{tet}}} = \frac{\sqrt{p_{0x} p_{1x} p_{0y} p_{1y}}}{h_x h_y \sqrt{n}} = \frac{\sqrt{(.45)(.55)(.5)(.5)}}{(.3958)(.3989)\sqrt{200}} = .111 \quad (\text{Equation 28.53})$$

The value $s_{r_{\text{tet}}} = .111$ is substituted in Equation 28.54, which is employed to evaluate the null hypothesis $H_0: r_{\text{tet}} = 0$. Use of the normal distribution in evaluating the null hypothesis assumes that the computation of r_{tet} is based on a large sample size (since, as noted earlier, r_{tet} will be extremely unreliable if it is based on a small sample). Employing Equation 28.54, the value $z = -4.14$ is computed. Note that the sign of z will always be the same as the sign of r_{tet} .

$$z = \frac{r_{\text{tet}}}{s_{r_{\text{tet}}}} = \frac{-.46}{.111} = -4.14 \quad (\text{Equation 28.54})$$

It will be assumed that the nondirectional alternative hypothesis $H_1: \rho_{\text{tet}} \neq 0$ is evaluated. Employing [Table A1](#), it is determined that the tabled critical two-tailed .05 and .01 values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$. Since the obtained absolute value $z = 4.14$ is greater than both of the aforementioned critical values, the nondirectional alternative hypothesis $H_1: \rho_{\text{tet}} \neq 0$ is supported at both the .05 and .01 levels. Additional discussion of the **tetrachoric correlation coefficient** can be found in Guilford (1965), Lindeman *et al.* (1980), and McNemar (1969).

2. Multiple regression analysis This section of the **Addendum** will describe the following measures: a) The **multiple correlation coefficient (Test 28k)**; b) The **partial correlation coefficient (Test 28l)**; and c) The **semi-partial correlation coefficient (Test 28m)**. The use of the term multivariate implies that data for three or more variables are employed in the analysis. The measures that are described are extensions of the **Pearson product-moment correlation coefficient** to an analysis involving three or more variables. All of the measures (each of which is discussed in reference to an analysis involving three variables) assume that all of the variables are measured on an interval/ratio scale. A brief description of the measures to be described follows.

The multiple correlation coefficient (Test 28k) The **multiple correlation coefficient** (R) is a correlation between a criterion variable and a linear combination of two or more predictor variables.

The partial correlation coefficient (Test 28l) The **partial correlation coefficient** (e.g., $r_{YX_1 \cdot X_2}$) measures the degree of association between two variables, after any linear association one or more additional variables has with the two variables has been removed.

The semi-partial correlation coefficient (Test 28m) The **semi-partial correlation coefficient** (or **part correlation coefficient**) (e.g., $r_{Y(X_1 \cdot X_2)}$) measures the degree of association between two variables, with the linear association of one or more other variables removed from only one of the two variables that are being correlated with one another.

General introduction to multiple regression analysis **Multiple regression analysis** is the term employed to describe the use of correlation and regression with designs involving more than two variables. Such analysis, which is considerably more complex than bivariate analysis, involves laborious computational procedures that make it all but impractical to conduct without the aid of a computer. Although this section will provide the reader with an overview of **multiple regression analysis**, the discussion to follow is not intended to provide comprehensive coverage

of the subject. For a more thorough discussion of multiple regression, the reader should consult sources on multivariate analysis (e.g., Marascuilo and Levin (1983), Stevens (1986, 1996), and Tabachnick and Fidell (1989, 1996)).

In contrast to simple linear regression, where scores on one predictor variable are employed to predict the scores on a criterion variable, in multiple regression analysis a researcher attempts to increase the accuracy of prediction through the use of multiple predictor variables. By employing multiple predictor variables, one can often account for a greater amount of the variability on the criterion variable than will be the case if only one of the predictor variables is employed. Thus, the major goal of multiple regression analysis is to identify a limited number of predictor variables which optimize one's ability to predict scores on a criterion variable.

Since researchers generally want the simplest possible predictive model (as well as the fact that from a time and cost perspective, a model that involves a limited number of variables is less costly and easier to implement), it is unusual to find a multiple regression model that involves more than five predictor variables. Two additional factors which limit the number of predictor variables derived in multiple regression analysis follow: a) Once a limited number of predictor variables has been identified that explains a relatively large proportion of the variability on the criterion variable, it becomes increasingly unlikely that any new predictor variables which are identified will result in a significant increase in predictive power; and b) Although the researcher wants to identify predictor variables that are highly correlated with the criterion variable, he also wants to make sure that the predictor variables employed account for different proportions of the variability on the criterion variable. In order to accomplish the latter, none of the predictor variables should be highly correlated with one another, since, if the latter is true, the variables will be redundant with respect to the variation on the criterion variable they explain. As a general rule, it is difficult to find a large number of predictor variables that are highly correlated with a criterion variable, yet not correlated with one another. The term **multicollinearity** is used to describe a situation where predictor variables have a high intercorrelation with one another. When multicollinearity exists, the reliability of multiple regression analysis may be severely compromised.

Within the framework of multiple regression analysis there are a variety of strategies that are employed in selecting predictor variables. Among the strategies that are available are the following: a) **Forward selection** — In **forward selection**, predictor variables are determined one at a time with respect to the order of their contribution in explaining variability on the criterion variable; b) **Backward selection** — In **backward selection**, the researcher starts with a large pool of predictor variables and, starting with the smallest contributor, eliminates them one at a time, based on whether or not they make a significant contribution to the predictive model; c) **Stepwise regression** — **Stepwise regression** is a combination of the forward and backward selection methods. In stepwise regression, one employs the forward selection method, but upon adding each new predictor variable, all of the remaining predictor variables from the original pool are reexamined to determine whether they should be retained in the predictive model; d) **Hierarchical regression** — Whereas in the three previous methods statistical considerations dictate which predictor variables are included in the model, in **hierarchical regression** the researcher determines which variables should be included in the model. The latter determination is based on such factors as logic, theory, results of prior research, and cost; and e) **Standard or direct regression** — In **standard/direct regression**, all available predictor variables are included in the model, including those that only explain a minimal amount of variability on the criterion variable. This type of regression may be employed when a researcher wants to explore, for theoretical or other reasons, the relationship between a large set of predictor variables and a criterion variable. Standard/direct regression is atypical when compared with the other methods of regression analysis, in that it is more likely to result in a large number of predictor variables.

Upon conducting a multiple regression analysis, it is recommended that the resulting regression model be **cross-validated**. Minimally, this means replicating the results of the analysis on two subsamples, each representing a different half of the original sample. An even more desirable strategy is replicating the results on one or more independent samples that are representative of the population to which one wishes to apply the model. By cross-validating a model, one can demonstrate that it generates consistent results, and will thus be of practical value in making predictions among members of the reference population upon which the model is based.

Although multiple regression analysis may result in a mechanism for reasonably accurate predictions, it does not provide sufficient control over the variables under study to allow a researcher to draw conclusions with regard to cause and effect. As is the case with bivariate correlation, multivariate correlation is not immune to the potential impact of extraneous variables that may be critical in understanding the causal relationship between the variables under study. In order to demonstrate cause and effect, one must employ the experimental method (specifically, through use of the **true experiment**, demonstrate a causal connection between scores on a dependent variable and a manipulated independent variable). It should be noted that there is a procedure called **path analysis** (which will not be described in this book) that employs correlational information to evaluate causal relationships between variables. Statisticians are not in agreement, however, with respect to what role path analysis (as well as a number of related procedures) should play in making judgements with regard to cause and effect in correlational research.

Multiple regression analysis has a number of assumptions which if violated can compromise the reliability of the results. These assumptions (which concern normality, linearity, homoscedasticity, and independence of the residuals), as well as the impact of **outliers** on a multiple regression analysis, are discussed in books that provide comprehensive coverage of the subject.

Computational procedures for multiple regression analysis involving three variables

Test 28k: The multiple correlation coefficient Within the framework of multiple regression analysis, a researcher is able to compute a correlation coefficient between the criterion variable and the k predictor variables (where $k \geq 2$). The computed **multiple correlation coefficient** is represented by the notation R . A computed value of R must fall within the range 0 to +1 (i.e., $0 \leq R \leq +1$). Unlike an r value computed for two variables, the **multiple correlation coefficient** cannot be a negative number. The closer the value of R is to 1, the stronger the linear relationship between the criterion variable and the k predictor variables, whereas the closer it is to 0, the weaker the linear relationship. Because of the complexity of the computations involved, the discussion of the computational procedures for multiple regression analysis will be restricted to designs involving two predictor variables (which in the examples to be discussed will be designated X_1 and X_2), and a criterion variable (which will be designated Y). When $k = 2$, Equation 28.55 is employed to compute the value of R . The notation $R_{Y.X_1X_2}$ represents the **multiple correlation coefficient** between the criterion variable Y and the linear combination of two predictor variables X_1 and X_2 .

$$R_{Y.X_1X_2} = \sqrt{\frac{r_{YX_1}^2 + r_{YX_2}^2 - 2r_{YX_1}r_{YX_2}r_{X_1X_2}}{1 - r_{X_1X_2}^2}} \quad (\text{Equation 28.55})$$

The following example will be employed to illustrate the use of Equation 28.55. Assume that the following correlation coefficients have been computed: a) The correlation between the number of ounces of sugar a child eats (which will represent predictor variable X_1) and the

number of cavities (which will represent the criterion variable Y) is $r_{YX_1} = .955$; b) The correlation between the number of ounces of salt a child eats (which will represent predictor variable X_2) and the number of cavities is $r_{YX_2} = .52$; and c) The correlation between the number of ounces of sugar a child eats and the number of ounces of salt a child eats is $r_{X_1X_2} = .37$. The three above noted correlations are based on the following data: a) Table 28.1 lists the number of ounces of sugar a child eats (X_1) and the number of cavities (Y); and b) The following values, which are used to compute the correlations $r_{YX_2} = .52$ and $r_{X_1X_2} = .37$, are employed to represent the number of ounces of salt eaten (X_2) by the five subjects in Table 28.1: 4, 1, 1, 3, 6. Employing the latter set of five scores, the mean and estimated population standard deviation for variable X_2 are $\bar{X}_2 = 15/5 = 3$ and $\hat{s}_{X_2} = [63 - ((15)^2/5)]/4 = 2.12$.

Substituting the correlations $r_{YX_1} = .955$, $r_{YX_2} = .52$, and $r_{X_1X_2} = .37$ in Equation 28.55, the multiple correlation coefficient $R_{Y.X_1X_2} = .972$ is computed.

$$R_{Y.X_1X_2} = \sqrt{\frac{(.955)^2 + (.52)^2 - 2(.955)(.52)(.37)}{1 - (.37)^2}} = \sqrt{.944} = .972$$

Note that the value $R_{Y.X_1X_2} = .972$ is larger than either value that is computed when each of the predictor variables is correlated separately with the criterion variable. Of course, the value of $R_{Y.X_1X_2}$ can be only minimally above $r_{YX_1} = .955$, since the maximum value R can attain is 1.

The coefficient of multiple determination R^2 , which is the square of the **multiple correlation coefficient**, is referred to as the **coefficient of multiple determination**. The **coefficient of multiple determination** indicates the proportion of variance on the criterion variable that can be accounted for on the basis of variability on the k predictor variables. In our example $R^2_{Y.X_1X_2} = (.972)^2 = .944$. In point of fact, R^2 is a biased measure of P^2 , which is the population parameter it is employed to estimate (P is the upper case Greek letter **rho**). The degree to which the computed value of R^2 is a biased estimate of P^2 will be a function of the sample size and the number of predictor variables employed in the analysis. The value of R^2 will be spuriously inflated when the sample size is close in value to the number of predictor variables employed in the analysis.²⁵ For this reason, sources emphasize that the number of subjects employed in a multiple regression analysis should always be substantially larger than the number of predictor variables. For example, Marascuilo and Levin (1983) recommend that the value of n should be at least ten times the value of k .²⁶

One way of correcting for bias resulting from a small sample size is to employ Equation 28.56 to compute \tilde{R}^2 , which is a relatively unbiased estimate of P^2 . The value \tilde{R}^2 is commonly referred to as a “shrunk” estimate of the **coefficient of multiple determination**.²⁷

$$\tilde{R}^2 = 1 - \frac{(1 - R^2)(n - 1)}{n - k - 1} \quad \text{(Equation 28.56)}$$

It can be seen below that substituting the values from our example in Equation 28.56 yields the value $\tilde{R}^2_{Y.X_1X_2} = .89$, which is lower than $R^2_{Y.X_1X_2} = .944$ computed with Equation 28.55 ($R^2_{Y.X_1X_2} = .944$ is the value in the radical of Equation 28.55 prior to computing the square root).

$$\tilde{R}^2_{Y.X_1X_2} = 1 - \frac{[1 - (.944)][5 - 1]}{5 - 2 - 1} = .89$$

Test 28k-a: Test of significance for a multiple correlation coefficient Equation 28.57 is employed to evaluate the null hypothesis $H_0: P^2 = 0$. If the latter null hypothesis is supported, the value of P will also equal zero and, consequently, the null hypothesis $H_0: P = 0$ is also supported.

$$F = \frac{(n - k - 1)R^2}{k(1 - R^2)} \quad (\text{Equation 28.57})$$

The computed value $R_{Y.X_1X_2}^2 = .944$, as well as the shrunken estimate $\hat{R}_{Y.X_1X_2}^2 = .89$, is substituted in Equation 28.57 below. If one has to choose which of the two values to employ, researchers would probably consider it more prudent to employ the shrunken estimate $\hat{R}_{Y.X_1X_2}^2 = .89$ (especially when the sample size is small).

$$F = \frac{(5 - 2 - 1)(.944)}{2(1 - .944)} = 16.86$$

$$F = \frac{(5 - 2 - 1)(.89)}{2(1 - .89)} = 8.09$$

The computed F value is evaluated with **Table A10 (Table of the F Distribution)** in the **Appendix**. In order to reject the null hypothesis, the F value must be equal to or greater than the tabled critical value at the prespecified level of significance. The degrees of freedom employed for the analysis are $df_{\text{num}} = k$ and $df_{\text{den}} = n - k - 1$. Thus, for our example $df_{\text{num}} = 2$ and $df_{\text{den}} = 5 - 2 - 1 = 2$. In **Table A10**, for $df_{\text{num}} = 2$ and $df_{\text{den}} = 2$, the tabled critical .05 and .01 values are $F_{.05} = 19.00$ and $F_{.01} = 99.00$. Since both of the obtained values $F = 16.86$ and $F = 8.09$ are less than $F_{.05} = 19.00$, regardless of whether R^2 or \hat{R}^2 is computed, the null hypothesis cannot be rejected. Thus, in spite of the fact that the obtained value of R is close to 1, the data still do not allow one to conclude that the population multiple correlation coefficient is some value other than zero. The lack of significance for such a large R value can be attributed to the small sample size.

The multiple regression equation A major goal of multiple regression analysis is to derive a **multiple regression equation** that utilizes scores on the k predictor variables to predict the scores of subjects on the criterion variable. Equation 28.58 is the general form of the multiple regression equation.

$$Y' = a + b_1 X_1 + b_2 X_2 + \cdots + b_k X_k \quad (\text{Equation 28.58})$$

Note that the multiple regression equation contains a **regression coefficient** (b_i) for each of the predictor variables (X_1, X_2, \dots, X_k) and a **regression constant** (a). In contrast to the regression line employed in simple linear regression, the multiple regression equation describes a **regression plane** that provides the best fit through a set of data points that exists in a **multi-dimensional space**. The values computed for the regression equation minimize the sum of the squared residuals, which in the case of multiple regression are the sum of the squared distances of all the data points from the regression plane.

Equations 28.59 and 28.60 can be employed to determine the values of the regression coefficients b_1 and b_2 , which are the coefficients for predictor variables X_1 and X_2 . Each of the regression coefficients indicates the amount of change on the criterion variable Y that will be associated with a one unit change on that predictor variable, if the effect of the second predictor variable is held constant.

$$b_1 = \left[\frac{\bar{s}_Y}{\bar{s}_{X_1}} \right] \left[\frac{r_{YX_1} - r_{YX_2} r_{X_1 X_2}}{1 - r_{X_1 X_2}^2} \right] \quad (\text{Equation 28.59})$$

$$b_2 = \left[\frac{\bar{s}_Y}{\bar{s}_{X_2}} \right] \left[\frac{r_{YX_2} - r_{YX_1} r_{X_1 X_2}}{1 - r_{X_1 X_2}^2} \right] \quad (\text{Equation 28.60})$$

Equation 28.61 is employed to compute the regression constant a (which is analogous to the Y intercept computed in simple linear regression).

$$a = \bar{Y} - b_1 \bar{X}_1 - b_2 \bar{X}_2 \quad (\text{Equation 28.61})$$

The multiple regression equation will now be computed. From earlier discussion we know the following values: $\bar{X}_1 = 7.2$, $\bar{s}_{X_1} = 8.58$, $\bar{X}_2 = 3$, $\bar{s}_{X_2} = 2.12$, $\bar{Y} = 3.4$, $\bar{s}_Y = 2.70$, $r_{YX_1} = .955$, $r_{YX_2} = .52$, $r_{X_1 X_2} = .37$. Substituting the appropriate values in Equations 28.59–28.61, the multiple regression equation is determined below.

$$b_1 = \left[\frac{2.70}{8.58} \right] \left[\frac{.955 - (.52)(.37)}{1 - (.37)^2} \right] = .278$$

$$b_2 = \left[\frac{2.70}{2.12} \right] \left[\frac{.52 - (.955)(.37)}{1 - (.37)^2} \right] = .246$$

$$a = 3.4 - (.278)(7.2) - (.246)(3) = .660$$

$$Y' = .660 + .278X_1 + .246X_2$$

To illustrate the application of the multiple regression equation, when the appropriate values are substituted in Equation 28.58, a child who consumes 4 ounces of sugar (X_1) and 2 ounces of salt (X_2) per week is predicted to have 2.264 cavities.

$$Y' = .660 + (.278)(4) + (.246)(2) = 2.264$$

The standard error of multiple estimate As is the case with simple linear regression, a **standard error of estimate** can be computed which can be employed to determine how accurately the multiple regression equation will predict a subject's score on the criterion variable. Employing this error term, which in the case of multiple regression is referred to as the **standard error of multiple estimate**, one can compute a confidence interval for a predicted score. The standard error of multiple estimate will be represented by the notation $s_{Y \cdot X_1 X_2}$. Equation 28.62 is employed to compute $s_{Y \cdot X_1 X_2}$ if R^2 (the biased estimate of P^2) is used to represent the **coefficient of multiple determination**.²⁸ If, on the other hand, the unbiased estimate \bar{R}^2 is employed to represent the **coefficient of multiple determination**, Equation 28.63 can be used to compute $s_{Y \cdot X_1 X_2}$. The two equations are employed below to compute the value $s_{Y \cdot X_1 X_2} = .90$.

$$(\text{Equation 28.62})$$

$$s_{Y \cdot X_1 X_2} = \bar{s}_Y \sqrt{\left[\frac{n - 1}{n - k - 1} \right] (1 - R_{Y \cdot X_1 X_2}^2)} = (2.70) \sqrt{\left[\frac{5 - 1}{5 - 2 - 1} \right] (1 - .944)} = .90$$

$$s_{Y.X_1X_2} = \bar{s}_Y \sqrt{1 - \bar{R}_{Y.X_1X_2}^2} = (2.70) \sqrt{1 - .89} = .90 \quad (\text{Equation 28.63})$$

Computation of a confidence interval for Y' Equation 28.64 (which is analogous to Equation 28.16) can be employed to compute a confidence interval for the predicted value Y' . The value $s_{Y.X_1X_2} = .90$ is employed in Equation 28.64 to compute the 95% confidence interval for the subject who is predicted to have $Y' = 2.264$ cavities. Also employed in the latter equation is the tabled critical two-tailed .05 t value $t_{.05} = 4.30$ (for $df = n - k - 1 = 5 - 2 - 1 = 2$), which delineates to the 95% confidence interval.

$$(\text{Equation 28.64})$$

$$CI_{(1-\alpha)} = Y' \pm (t_{\alpha/2})(s_{Y.X_1X_2}) = 2.264 \pm (4.30)(.90) = 2.264 \pm 3.87$$

This result indicates that the researcher can be 95% confident (or the probability is .95) that the number of cavities the subject actually has falls within the range -1.606 and 6.134 (i.e., $-1.606 \leq Y \leq 6.134$). Since a person cannot have a negative number of cavities, the latter result indicates that the person will have between 0 and 6.134 cavities.

Evaluation of the relative importance of the predictor variables If the result of a multiple regression analysis is significant, a researcher will want to assess the relative importance of the predictor variables in explaining variability on the criterion variable. It should be noted that although the value computed for the **multiple correlation coefficient** is not significant for the example under discussion, within the framework of the discussion of the material in this section, it will be assumed that it is. Intuitively, it might appear that one can evaluate the relative importance of the predictor variables based on the relative magnitude of the regression coefficients. However, since the different predictor variables represent different units of measurement, comparison of the regression coefficients will not allow a researcher to make such an estimate. One approach to solving this problem is to standardize each of the variables so that scores on all of the variables are based on standard normal distributions. As a result of standardizing all of the variables, Equation 28.65 (which is referred to as the **standardized multiple regression equation**) becomes the general form of the multiple regression equation.

$$z_{Y'} = \beta_1 z_1 + \beta_2 z_2 + \cdots + \beta_k z_k \quad (\text{Equation 28.65})$$

In Equation 28.65 the predicted value Y' , as well as the scores on the predictor variables X_1 and X_2 , are expressed as standard deviation scores (i.e., $z_{Y'}$, z_1 , z_2). The standardized equivalent of a regression coefficient, referred to as a **beta weight**, is represented by the notation β_i . Since the regression constant a will always equal zero in the standardized multiple regression equation, it is not included. When there are two predictor variables, Equations 28.66 and 28.67 can be employed to compute the values of β_1 and β_2 . Note that each equation is expressed in two equivalent forms, one form employing the regression coefficients and the relevant estimated population standard deviations, and the other form employing the correlations between the three variables.

$$\beta_1 = b_1 \frac{\bar{s}_{X_1}}{\bar{s}_{Y'}} = \frac{r_{YX_1} - r_{YX_2} r_{X_1X_2}}{1 - r_{X_1X_2}^2} \quad (\text{Equation 28.66})$$

$$\beta_2 = b_2 \left[\frac{\bar{s}_{X_2}}{\bar{s}_Y} \right] = \frac{r_{YX_2} - r_{YX_1} r_{X_1 X_2}}{1 - r_{X_1 X_2}^2} \quad (\text{Equation 28.67})$$

Substituting the appropriate values in Equations 28.66 and 28.67, the values $\beta_1 = .883$ and $\beta_2 = .193$ are computed.

$$\beta_1 = .278 \left[\frac{8.58}{2.70} \right] = \frac{.955 - (.52)(.37)}{[1 - (.37)^2]} = .883$$

$$\beta_2 = .246 \left[\frac{2.12}{2.70} \right] = \frac{.52 - (.955)(.37)}{[1 - (.37)^2]} = .193$$

Thus, the standardized multiple regression equation is as follows: $z_{Y'} = .883z_1 + .193z_2$. The value $\beta_1 = .883$ indicates that an increase of one standard deviation unit on variable X_1 is associated with an increase of .883 standard deviation units on the criterion variable (if the predictor variable X_2 remains at a fixed value). In the same respect the value $\beta_2 = .193$ indicates that an increase of one standard deviation unit on variable X_2 is associated with an increase of .193 standard deviation units on the criterion variable (if the predictor variable X_1 remains at a fixed value).

When there are two predictor variables, Equation 28.68 employs the standardized beta weights to provide an alternative method for computing the value $R_{Y, X_1 X_2}^2$. The value derived with Equation 28.68 will be equivalent to the square of the value computed with Equation 28.55.

$$R_{Y, X_1 X_2}^2 = \beta_1 r_{YX_1} + \beta_2 r_{YX_2} \quad (\text{Equation 28.68})$$

$$R_{Y, X_1 X_2}^2 = (.883)(.955) + (.193)(.52) = .944$$

Some sources note that the absolute values of the beta weights reflect the rank-ordering of the predictor variables with respect to the role they play in accounting for variability on the criterion variable. Kachigan (1986) suggests that by dividing the square of a larger beta weight by the square of a smaller beta weight, a researcher can determine the relative influence of two predictor variables on the criterion variable. The problem with the latter approach (as Kachigan (1986) himself notes) is that beta weights do not allow a researcher to separate the joint contribution of two or more predictor variables. The fact that predictor variables are usually correlated with one another (as is the case in the example under discussion), makes it difficult to determine how much variability on the criterion variable can be accounted for by any single predictor variable in and of itself. In view of this, Howell (1992, 1997) and Marascuilo and Serlin (1988) note that statisticians are not in agreement with respect to what, if any, methodology is appropriate for determining the precise amount of variability attributable to each of the predictor variables.

Evaluating the significance of a regression coefficient In conducting a multiple regression analysis it is common practice to evaluate whether each of the regression coefficients is statistically significant. Since the unstandardized/raw score coefficients and standardized coefficients are linear transformations of one another, a statistical test on either set of coefficients will yield the same result. The null hypothesis that is evaluated is that the true value of the regression coefficient in the population equals zero. Thus, $H_0: B_i = 0$ (where B_i , which is the upper case Greek letter **beta**, represents the value of the coefficient for the i^{th} predictor variable in the underlying population). For the purpose of discussion it will be assumed that the aforementioned null

hypothesis is stated in reference to the unstandardized coefficients. In order to evaluate the null hypothesis $H_0: B_i = 0$, a standard error of estimate must be computed for a coefficient. When there are two predictor variables, the standard error of estimate for an unstandardized coefficient (represented by the notation s_{b_i}) is computed with Equation 28.69.²⁹

$$s_{b_i} = \frac{\tilde{s}_Y}{\tilde{s}_{X_i}} \sqrt{\frac{1 - R_{Y.X_1X_2}^2}{(1 - r_{X_1X_2}^2)(n - k - 1)}} \quad (\text{Equation 28.69})$$

Employing Equation 28.69, the values $s_{b_1} = .057$ and $s_{b_2} = .229$ are computed.

$$s_{b_1} = \frac{2.70}{8.58} \sqrt{\frac{1 - .944}{[1 - (.37)^2][5 - 2 - 1]}} = .057$$

$$s_{b_2} = \frac{2.70}{2.12} \sqrt{\frac{1 - .944}{[1 - (.37)^2][5 - 2 - 1]}} = .229$$

Each of the values $s_{b_1} = .057$ and $s_{b_2} = .229$ can be substituted in Equation 28.70, which employs the t distribution to evaluate the null hypothesis $H_0: B_i = 0$.³⁰ In the analysis to be described it will be assumed that the nondirectional alternative hypothesis $H_1: B_i \neq 0$ is evaluated for each regression coefficient. The degrees of freedom employed in evaluating a t value computed with Equation 28.70 are $df = n - k - 1$. Thus, $df = 5 - 2 - 1 = 2$. If the null hypothesis cannot be rejected for a specific coefficient, the researcher can conclude that the predictor variable in question will not be of any use in predicting scores on the criterion variable.

$$t_{b_i} = \frac{b_i}{s_{b_i}} \quad (\text{Equation 28.70})$$

Employing Equation 28.70, the null hypotheses $H_0: B_1 = 0$ and $H_0: B_2 = 0$ are evaluated.³¹

$$t_{b_1} = \frac{.278}{.057} = 4.88 \quad t_{b_2} = \frac{.246}{.229} = 1.07$$

Employing **Table A2**, for $df = 2$, the tabled critical .05 and .01 t values are $t_{.05} = 4.30$ and $t_{.01} = 9.93$.³² Since the value $t_{b_1} = 4.88$ is greater than $t_{.05} = 4.30$, the nondirectional alternative hypothesis $H_1: B_1 \neq 0$ is supported at the .05 level. It is not supported at the .01 level, since $t_{b_1} = 4.88$ is less than $t_{.01} = 9.93$. Since $t_{b_2} = 1.07$ is less than $t_{.05} = 4.30$, the nondirectional alternative hypothesis $H_1: B_2 \neq 0$ is not supported. Thus, we can conclude that, whereas predictor variable X_1 (sugar consumption) contributes significantly in predicting variability on the criterion variable (number of cavities), predictor variable X_2 (salt consumption) does not. Consequently, the latter predictor variable can be removed from the analysis. It should be noted that when a researcher elects to eliminate a predictor variable from the analysis, a new regression equation should be derived which just involves the data for the remaining predictor variable(s).

Computation of a confidence interval for a regression coefficient Equation 28.71 can be employed to compute a confidence interval for a regression coefficient.

$$CI_{b_i(1-\alpha)} = b_i \pm (t_{\alpha/2})(s_{b_i}) \quad \text{(Equation 28.71)}$$

Using Equation 28.71, the 95% confidence intervals for the two regression coefficients are computed. The t value employed in Equation 28.71 is $t_{.05} = 4.30$, which is the tabled critical two-tailed .05 t value for $df = n - k - 1 = 5 - 2 - 1 = 2$.

$$CI_{.95_{b_1}} = .278 \pm (4.30)(.057) = .278 \pm .245$$

$$CI_{.95_{b_2}} = .246 \pm (4.30)(.229) = .246 \pm .985$$

Thus, the range of values in which the researcher can be 95% confident (or the probability is .95) the true values of the coefficients lie are as follows: $.033 \leq B_1 \leq .523$ and $-.739 \leq B_2 \leq 1.231$.

Partial and semipartial correlation Within the framework of multiple regression analysis there are a number of other types of correlation coefficients which can be computed that can further clarify the nature of the relationship between predictor variables and a criterion variable. In evaluating the relationship between a criterion variable and a single predictor variable, it is not uncommon that the correlation is influenced by a third variable. As an example, the relationship between frequency of violent crimes (which will represent the criterion variable Y) and level of stress (which will represent the predictor variable X_1) is undoubtedly influenced by extraneous variables such as social class, which if included in a multiple regression analysis can represent a second potential predictor variable X_2 . In some instances, by measuring the influence of a third variable (in this case social class), a researcher will be better able to understand the nature of the relationship between the other two variables (violent crime and stress). By allowing the third variable to serve in the role of a mediating variable, it often increases the researcher's ability to predict the scores of subjects on the criterion variable. In other instances, however, the researcher may view the contribution of a third variable as interfering with the study of the relationship between the other two variables. Thus, if a researcher wants to obtain a "purer" measure of the relationship between violent crime and stress, he might want to eliminate the influence of social class from the analysis. In instances where one wants to control for the influence of an extraneous variable, the latter variable is viewed as a **nuisance variable**. Fortunately, correlational procedures have been developed which allow researchers to statistically control for the influence of extraneous variables. Two of these procedures, **partial correlation** and **semipartial correlation** (also referred to as **part correlation**), are described in this section.

Test 281: The partial correlation coefficient A **partial correlation coefficient** allows a researcher to measure the degree of association between two variables, after any linear association one or more additional variables have with the other two variables has been removed. Partial correlation reverses that which multiple correlation accomplishes. Whereas multiple correlation combines variables in order to assess their cumulative effect, partial correlation removes the effects of variables in order to determine what effect remains when one or more of the variables have been eliminated.

In the case of two predictor variables X_1 and X_2 and the criterion variable Y , the **partial correlation coefficient** $r_{YX_1 \cdot X_2}$ represents the correlation between Y and X_1 after any linear association that X_2 has with either Y or X_1 has been removed. It can also be stated that the **partial**

correlation coefficient $r_{YX_1 \cdot X_2}$ represents the correlation between Y and X_1 if X_2 is held constant. By computing the **partial correlation coefficient** $r_{YX_1 \cdot X_2}$, one is able to have a “purer” measure of the relationship between a criterion variable Y and the predictor variable X_1 .

When there are three variables, it is possible to compute the following **partial correlation coefficients**: $r_{YX_1 \cdot X_2}$, $r_{YX_2 \cdot X_1}$, $r_{X_1 X_2 \cdot Y}$. Equation 28.72 is the general equation for computing a **partial correlation coefficient** involving three variables (where A , B , and C represent the three variables). The notation $r_{AB \cdot C}$ represents the correlation between A and B , after any linear relationship C has with A and B has been removed.

$$r_{AB \cdot C} = \frac{r_{AB} - r_{AC}r_{BC}}{\sqrt{(1 - r_{AC}^2)(1 - r_{BC}^2)}} \quad (\text{Equation 28.72})$$

Employing Equation 28.72, the **partial correlation coefficients** $r_{YX_1 \cdot X_2}$ (which is the partial correlation of Y and X_1 , with the effect of X_2 removed) and $r_{YX_2 \cdot X_1}$ (which is the partial correlation of Y and X_2 , with the effect of X_1 removed) will be computed. When the appropriate correlations from the example involving the relationship between sugar and salt consumption and the number of cavities are substituted in Equation 28.72, the **partial correlation coefficients** $r_{YX_1 \cdot X_2} = .96$ and $r_{YX_2 \cdot X_1} = .60$ are computed.

$$r_{YX_1 \cdot X_2} = \frac{r_{YX_1} - r_{YX_2}r_{X_1 X_2}}{\sqrt{(1 - r_{YX_2}^2)(1 - r_{X_1 X_2}^2)}} = \frac{.955 - (.52)(.37)}{\sqrt{[1 - (.52)^2][1 - (.37)^2]}} = .96$$

$$r_{YX_2 \cdot X_1} = \frac{r_{YX_2} - r_{YX_1}r_{X_1 X_2}}{\sqrt{(1 - r_{YX_1}^2)(1 - r_{X_1 X_2}^2)}} = \frac{.52 - (.955)(.37)}{\sqrt{[1 - (.955)^2][1 - (.37)^2]}} = .60$$

The value $r_{YX_1 \cdot X_2} = .96$ indicates that the correlation between sugar consumption and the number of cavities, with salt consumption removed, is .96. The value $r_{YX_2 \cdot X_1} = .60$ indicates that the correlation between salt consumption and the number of cavities, with sugar consumption removed, is .60. Although the partial correlation between two variables is generally (but not always) smaller than the **zero order correlation** (which is the term that refers to the correlation between the two variables before the effect of the third variable has been removed), this is not the case in the example under discussion (since the partial correlations $r_{YX_1 \cdot X_2} = .96$ and $r_{YX_2 \cdot X_1} = .60$ are larger than the **zero order correlations** $r_{YX_1} = .955$ and $r_{YX_2} = .52$). When a partial correlation is substantially different from the corresponding zero order correlation (especially when the absolute value of the partial correlation is substantially larger), it may indicate the presence of a **suppressor variable**. A **suppressor variable** is a predictor variable that can improve prediction on the criterion variable by suppressing variance that is irrelevant to predicting the criterion variable. In a set of three variables, a suppressor variable is a predictor variable (X_i) that has a low correlation with the criterion variable (Y), but a high correlation with the other predictor variable (X_j). By virtue of the latter, inclusion of the suppressor variable in the analysis may result in a multiple correlation coefficient ($R_{Y \cdot X_i X_j}$) that has a larger absolute value (or even a different sign) than the zero order correlation coefficient between the criterion variable and the suppressor variable (r_{YX_i}). It should be noted that suppressor variables can create major problems in interpreting the results of a multiple regression analysis. For a more detailed discussion of suppressor variables the reader is referred to Cohen and Cohen (1983).

The square of a partial correlation coefficient represents the proportion of variability explained on the criterion variable by one of the predictor variables, after removing any linear effects of the other predictor variable from the other two variables. In the case of $r_{YX_1 \cdot X_2} = .96$, $r_{YX_1 \cdot X_2}^2 = (.96)^2 = .92$. Thus, 92% of the variability on the criterion variable can be accounted for on the basis of the predictor variable X_1 , when the linear effects of variable X_2 are removed from the other two variables. In the case of $r_{YX_2 \cdot X_1} = .60$, $r_{YX_2 \cdot X_1}^2 = (.60)^2 = .36$. Thus, 36% of the variability on the criterion variable can be accounted for on the basis of the predictor variable X_2 , when the linear effects of variable X_1 are removed from the other two variables.

Test 28l-a: Test of significance for a partial correlation coefficient The null hypothesis $H_0: \rho_p = 0$ can be evaluated with Equation 28.73 (where ρ_p represents the population **partial correlation coefficient**).³³

$$t = \frac{r_p \sqrt{n - v}}{\sqrt{1 - r_p^2}} \quad (\text{Equation 28.73})$$

Where: r_p is the **partial correlation coefficient**
 v is the total number of variables employed in the analysis

When there are two predictor variables and one criterion variable, the total number of variables employed in the analysis is 3, and thus $\sqrt{n - v} = \sqrt{n - 3}$. The value $n - v = n - 3$ represents the number of degrees of freedom employed for the analysis.³⁴ Employing Equation 28.73, the null hypothesis is evaluated in reference to the partial correlation coefficients $r_{YX_1 \cdot X_2} = .96$ and $r_{YX_2 \cdot X_1} = .60$.

$$t = \frac{(.96)\sqrt{5 - 3}}{\sqrt{1 - (.96)^2}} = 4.85 \quad t = \frac{(.60)\sqrt{5 - 3}}{\sqrt{1 - (.60)^2}} = 1.06$$

It will be assumed that the nondirectional alternative hypothesis $H_1: \rho_p \neq 0$ is evaluated. Employing **Table A2**, for $df = 2$ (since $df = 5 - 3 = 2$), the tabled critical two-tailed .05 and .01 values are $t_{.05} = 4.30$ and $t_{.01} = 9.93$. Since the obtained value $t = 4.85$ is greater than $t_{.05} = 4.30$, the nondirectional alternative hypothesis $H_1: \rho_{YX_1 \cdot X_2} \neq 0$ is supported at the .05 level (but not at the .01 level). Since the obtained value $t = 1.06$ is less than $t_{.05} = 4.30$, the nondirectional alternative hypothesis $H_1: \rho_{YX_2 \cdot X_1} \neq 0$ is not supported.

When there are two predictor variables, a partial correlation can obviously only eliminate the effect of one other predictor variable. This kind of partial correlation is often referred to as a **first-order partial correlation**. When there are more than two predictor variables, it is possible to compute **higher-order partial correlations** in which the effects of two or more predictor variables are eliminated. Thus, a **second-order partial correlation** is one in which the effects of two predictor variables are eliminated. A discussion of higher-order partial correlation can be found in Cohen and Cohen (1983), Hays (1994), and Marascuilo and Levin (1983).

Test 28m: The semipartial correlation coefficient A **semipartial (or part) correlation coefficient** measures the degree of association between two variables, with the linear association of one or more other variables removed from only one of the two variables that are being correlated with one another. In the case of two predictor variables and a criterion variable, a semipartial correlation coefficient measures the degree of association between two variables, with

the influence of the third variable removed from only one of the two variables that are being correlated with one another. Thus, the **semipartial correlation coefficient** $r_{Y(X_1, X_2)}$ represents the correlation between Y and X_1 after any linear association that X_2 has with X_1 has been removed.

When there are three variables, it is possible to compute the following six **semipartial correlation coefficients**: $r_{Y(X_1, X_2)}$, $r_{Y(X_2, X_1)}$, $r_{X_1(Y, X_2)}$, $r_{X_1(X_2, Y)}$, $r_{X_2(Y, X_1)}$, $r_{X_2(X_1, Y)}$. Equation 28.74 is the general equation for computing a **semipartial correlation coefficient** involving three variables (where A , B , and C represent the three variables). The notation $r_{A(B, C)}$ represents the correlation between A and B , after any linear relationship that C has with B has been removed.

$$r_{A(B, C)} = \frac{r_{AB} - r_{AC}r_{BC}}{\sqrt{1 - r_{BC}^2}} \quad (\text{Equation 28.74})$$

Employing Equation 28.74, the **semipartial correlation coefficients** $r_{Y(X_1, X_2)} = .82$ and $r_{Y(X_2, X_1)} = .18$ are computed.

$$r_{Y(X_1, X_2)} = \frac{r_{YX_1} - r_{YX_2}r_{X_1X_2}}{\sqrt{1 - r_{X_1X_2}^2}} = \frac{.955 - (.52)(.37)}{\sqrt{1 - (.37)^2}} = .82$$

$$r_{Y(X_2, X_1)} = \frac{r_{YX_2} - r_{YX_1}r_{X_1X_2}}{\sqrt{1 - r_{X_1X_2}^2}} = \frac{.52 - (.955)(.37)}{\sqrt{1 - (.37)^2}} = .18$$

The square of a semipartial correlation coefficient represents the proportion of variability explained on one of the variables by a second variable, after removing the linear effect of a third variable from the second variable. In the case of $r_{Y(X_1, X_2)} = .82$, $r_{Y(X_1, X_2)}^2 = (.82)^2 = .67$. Thus, 67% of the variability on Y can be accounted for on the basis of X_1 when the linear effect of X_2 is removed from X_1 . In the case of $r_{Y(X_2, X_1)} = .18$, $r_{Y(X_2, X_1)}^2 = (.18)^2 = .03$. Thus, only 3% of the variability on Y can be accounted for on the basis of X_2 when the linear effect of X_1 is removed from X_2 .

Marascuilo and Serlin (1983) note that although it is theoretically possible for the two values to be equal (in reference to the same variables), a **semipartial correlation coefficient** will have a smaller absolute value than a **partial correlation coefficient**. The latter can be confirmed by the fact that the **partial correlation coefficient** $r_{YX_1, X_2} = .96$ is larger than the **semipartial correlation coefficient** $r_{Y(X_1, X_2)} = .82$, and the **partial correlation coefficient** $r_{YX_2, X_1} = .60$ is larger than the **semipartial correlation coefficient** $r_{Y(X_2, X_1)} = .18$.

Test 28m-a: Test of significance for a semipartial correlation coefficient The null hypothesis $H_0: \rho_{sp} = 0$ can be evaluated with Equation 28.75 (where ρ_{sp} represents the population **semipartial correlation coefficient**).³⁵

$$t = \frac{r_{sp}\sqrt{n - v}}{\sqrt{1 - r_{sp}^2}} \quad (\text{Equation 28.75})$$

Where: r_{sp} is the **semipartial correlation coefficient**
 v is the total number of variables employed in the analysis

When there are two predictor variables and one criterion variable, the total number of variables employed in the analysis is 3, and thus $\sqrt{n - v} = \sqrt{n - 3}$.³⁶ The value $n - v = n - 3$ represents the number of degrees of freedom employed for the analysis. Employing Equation 28.73, the null hypothesis is evaluated in reference to the **semipartial correlation coefficients** $r_{Y(X_1, X_2)} = .82$ and $r_{Y(X_2, X_1)} = .18$.

$$t = \frac{(.82)\sqrt{5 - 3}}{\sqrt{1 - (.82)^2}} = 2.03$$

$$t = \frac{(.18)\sqrt{5 - 3}}{\sqrt{1 - (.18)^2}} = .26$$

It will be assumed that the nondirectional alternative hypothesis $H_1: \rho_{sp} \neq 0$ is evaluated. Employing **Table A2**, for $df = 2$ (since $df = 5 - 3 = 2$), the tabled critical two-tailed .05 and .01 values are $t_{.05} = 4.30$ and $t_{.01} = 9.93$. Since both of the obtained t values are less than $t_{.05} = 4.30$, the nondirectional alternative hypotheses $H_1: \rho_{Y(X_1, X_2)} \neq 0$ and $H_1: \rho_{Y(X_2, X_1)} \neq 0$ are not supported.

Final comments on multiple regression analysis **Figure 28.7** (based on Cohen and Cohen (1983)), which is known as a **Venn diagram**, provides a visual summary of the proportion of variance represented by **zero order**, **multiple**, **partial**, and **semipartial correlation coefficients** (when there are two predictor variables and a criterion variable). Each of the three circles represents the variance of one of the three variables. Areas of overlap between circles represent shared variance between variables.

$$\text{Zero order correlations: } r_{Y, X_1}^2 = d + e \quad r_{Y, X_2}^2 = e + f \quad r_{X_1, X_2}^2 = e + b$$

$$\text{Multiple correlation: } R_{Y, X_1 X_2}^2 = d + e + f$$

$$\text{Partial correlations: } r_{YX_1, X_2}^2 = \frac{d}{d + g} \quad r_{YX_2, X_1}^2 = \frac{f}{f + g}$$

$$\text{Semipartial correlations: } r_{Y(X_1, X_2)}^2 = d \quad r_{Y(X_2, X_1)}^2 = f$$

Sources that provide comprehensive coverage of the general subject of multiple regression analysis (e.g., Cohen and Cohen (1983) and Marascuilo and Levin (1983), Stevens (1986, 1996), and Tabachnick and Fidell (1989, 1996)) describe additional analytical procedures (many of which involve matrix algebra), as well as covering other issues that are relevant to the interpretation of a such an analysis. It should also be noted that it is possible to conduct curvilinear multiple regression analysis, in which case a multiple regression equation is derived that uses a curvilinear combination of the predictor variables to predict scores on the criterion variable. As noted earlier, because of the tedious computations involved, multiple regression analysis is generally not practical to employ unless one has access to the appropriate computer software.

3. Additional multivariate procedures involving correlational analysis This section of the **Addendum** will describe a number of multivariate statistical procedures that directly or indirectly involve correlational analysis. The descriptions in this section are nonmathematical in nature, and only one procedure (**factor analysis**) is described in detail. Readers interested in comprehensive

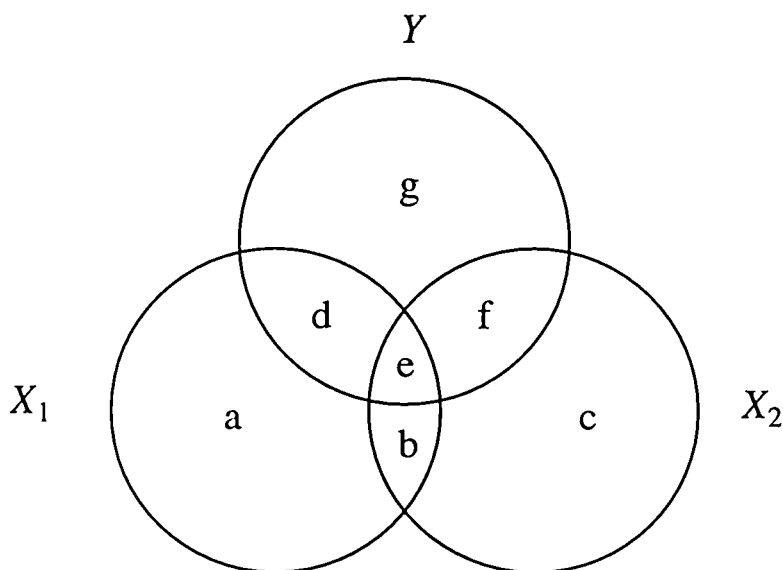


Figure 28.7 Venn Diagram of Variance Components Represented by Squared Correlation Coefficients

discussions of the procedures described in this section should consult sources that specialize in multivariate analysis. Two excellent references are Stevens (1986, 1996) and Tabachnick and Fidell (1989, 1996).

Factor analysis **Factor analysis** is one of a number multivariate statistical procedures discussed in the book. As noted under the discussion of the **Hotelling's T^2 test** (discussed in Section VII of the **t test for two independent samples**), the most general use of the term multivariate is in reference to procedures that evaluate experimental designs in which there are multiple independent variables and/or multiple dependent variables. **Factor analysis** is a statistical technique that is commonly employed in a broad spectrum of academic disciplines, in order to eliminate redundancy in a large body of data. To be more specific, in factor analysis a set of data which is comprised of many intercorrelated variables is transformed into a format that consists of a limited number of variables. The latter variables, which are referred to as **factors**, represent the basic underlying dimensions that are responsible for variability in the original set of data. Since the goal of factor analysis is to identify the basic elements that comprise a body of data, in many respects it is similar to breaking matter down into its basic elements. Just as by virtue of combining the existing chemical elements the chemist is able to account for all varieties of matter, in factor analysis it is assumed that when the derived factors (which are analogous to the elements) are combined with one another, they will allow a researcher to account for all or most of the variability in a set of data.

The description of factor analysis to be presented in this section is best categorized under the rubric of **exploratory factor analysis** (as opposed to **confirmatory factor analysis**, which is used to confirm that based on theory or preexisting empirical evidence, a set of data will conform to a specific factorial structure). **Exploratory factor analysis** employs a methodology referred to as **principal components analysis** (which is both mathematically and conceptually the simplest of the factor analytic procedures) to transform a body of data that is comprised of a large number of variables into a smaller set of variables (referred to as **factors** or **principal components**), which are linearly related to one another. The principal components/factors derived from the analysis should be minimal in number, yet at the same time should account for a large proportion of the variability in the original set of data.

To illustrate factor analysis, a simple example will be employed in which the procedure will be used to study the personality structure of human beings. When factor analysis is employed within the latter context, it is most commonly used to identify the most elementary traits that can be employed to describe personality. It should be noted, however, that factor analysis can be more limited in scope. For instance, one might take a single trait such as anxiety, and through the use of factor analysis determine if anxiety can be broken down into a limited number of more elementary components (e.g., anxiety based on fear of death or injury versus anxiety based on fear of psychologically threatening stimuli). The steps involved in factor analysis will now be described.

Step 1 — Accumulating the data: In conducting a factor analysis, the first thing a researcher must do is to select a set of measures to factor analyze. What set of measures the researcher will select will depend upon the nature of the problem one is studying. If the researcher wishes to identify the basic traits that can be employed to explain individual differences in personality, she should select a large number of measures which encompass all aspects of human behavior (which are a function of the personality). It is important to note that the specific types (as well as number) of measures a researcher selects will have a direct impact on the factors one will derive through use of factor analysis. The fact that two or more researchers employing factor analysis may reach different conclusions in studying the same subject matter can, among other things, be attributed to the fact that they may have employed different types of and/or amounts of data.

For purposes of illustration let us assume that a researcher wants to determine whether or not the traits measured by six commonly used personality tests can be expressed within the framework of a more limited number of dimensions. The researcher elects to employ factor analysis, since she believes there is considerable redundancy among the six tests. In order to conduct the factor analysis it is necessary that the researcher administers each of the six tests to a large number of people. In our example it will be assumed that 1000 people are employed, and that each person is administered six tests which measure the following traits: *Test A — Anxiety*; *Test B — Somatic Complaints*; *Test C — Guilt*; *Test D — Friendliness*; *Test E — Sensation Seeking*; *Test F — Dominance*.

Step 2 — Constructing the correlation matrix: Once scores are obtained for the 1000 subjects on each of the six tests, correlations are obtained between the scores of subjects on all six tests. The results of such an analysis can be summarized in a **correlation matrix**, which is a table that contains the values of the correlations between three or more measures. [Table 28.9](#) represents the correlation matrix for our example.

Table 28.9 Correlation Matrix (Personality Test Intercorrelations)

Test	A	B	C	D	E	F
A	—	.93	.86	.15	.21	.26
B	<i>x</i>	—	.83	.12	.18	.22
C	—	—	—	.05	.10	.13
D	—	—	—	—	.62	.72
E	—	—	—	—	—	.78
F	—	—	—	—	—	—

Each entry in [Table 28.9](#) represents the value of the correlation between two of the six tests. To determine the two tests represented by any of the correlations in the table, identify the letter at the left of the row and the letter at the top of the column in which a specific correlation appears. The row and column letters represent the two tests for which that correlation was computed. Thus, as an example, the correlation between *Test A* and *Test B* is .93, since $r = .93$ appears in

Row A and Column B. Note that correlations only appear in the upper half of the table, since the same information would be repeated in the lower half of the table (i.e., as an example, the correlation .93 would also appear in the cell with an x , which is in Row B and Column A). Note that the cells in the diagonal of table have been left blank. In actuality, a number (typically 1 or some other value) is employed in the diagonal cells, based upon certain defining characteristics of the type of factor analysis one is conducting.

Step 3 — Conducting the factor analysis: Factor analysis (which is impractical to conduct without a computer) is a complex statistical procedure that determines whether or not the data can be broken down into a more limited number of dimensions. The term factor derives from mathematics. Recollect in basic algebra where you were taught to factor an equation such as the one below.

$$(x^2 - y^2) = (x + y)(x - y)$$

By factoring the above equation one has broken it down into two basic elements, which, when combined, result in the equation. In the same respect, factor analysis of a correlation matrix, such as that depicted in [Table 28.9](#), will determine whether or not a more limited number of basic elements/dimensions can be employed to summarize and explain the information provided by the six tests. At this point it will be assumed that the appropriate mathematical operations associated with factor analysis (which are too complex to describe here) are conducted.

Step 4 — Interpreting the results of the factor analysis: [Table 28.10](#) summarizes the results of the factor analysis.

Table 28.10 Summary Table of Factor Analysis of Six Personality Tests

Test	Factor		Communality
	I	II	
A	.98	.13	.9773
B	.94	.09	.8917
C	.88	.01	.7745
D	.05	.76	.5801
E	.11	.81	.6682
F	.14	.94	.9032
Eigenvalue	2.6526	2.1424	Sum = 4.7950
Percent of Total Variance	44.21%	35.71%	

[Table 28.10](#) indicates that the factor analysis yielded two factors. This means that most of the variance in our data (i.e., individual differences between subjects) can be accounted for by the two derived factors. Note that in the columns for *Factor I* and *Factor II* are a set of numerical values. These values are called **factor loadings**. A factor loading is a correlation coefficient (and thus it will always fall within the range +1 to -1) that tells the researcher how much each of the variables (in this case, each of the tests) correlates with each of the factors. As is also the case with a correlation coefficient, the absolute value of a factor loading indicates the strength of the relationship between that factor and a given variable. The higher the absolute value of a factor loading, the more that variable contributes to that factor, or, to put it another way, the higher the factor loading, the purer a measure that variable is of that factor. Thus, *Test A* has a loading of .98 on *Factor I* and a loading of .13 on *Factor II*. This indicates that *Test A* is measuring *Factor I* to a much greater degree than it is measuring *Factor II*. By squaring the factor loading of a test, one can determine how much of the variance on the test can be accounted for by that factor. Thus, $(.98)^2 = .9604 = 96.04\%$ of the variance on *Test A* can be accounted for on the basis of *Factor I*, whereas *Factor II* only accounts for $(.13)^2 = .0169 = 1.69\%$ of the variance on *Test*

A. Taken together, *Factors I and II* account for 97.73% (i.e., 96.04% + 1.69%) of the variance on *Test A*. The value 97.73% (which expressed as a proportion = .9773) corresponds to the **communality** of the test (which is listed in the last column of [Table 28.10](#)). The concept of communality will be discussed in more detail later in this section.

Since all of the variance on *Test A* (as well as on the other five tests) is not accounted for on the basis of the two factors described in [Table 28.10](#), one might ask why only two factors have been employed in [Table 28.10](#) to describe the results of the factor analysis. Or, to put it another way, how does one decide how many factors to derive in a factor analysis?

As Kachigan (1986) notes, in interpreting the results of a factor analysis, a researcher must weigh **parsimony** against **comprehensiveness**. Thus, although the researcher wishes to account for as much of the variability in the data as possible (comprehensiveness), at the same time she wants to do it in the simplest possible manner (parsimony — i.e., with the fewest number of factors). There is no set rule with respect to how much of the total variance must be accounted for by the factors a researcher derives. (Stevens (1996) notes that some researchers attempt to account for a minimum of 70% of the variability.) In essence, how many factors one decides to employ will ultimately depend on the purpose for which one intends to use the results of a factor analysis. Those factors that explain the greatest amount of variability in the data almost always represent what are referred to as **common factors**. Common factors are factors that load on more than one of the variables. Those common factors which account for a substantial amount of the variability are designated as **significant factors** in a factor analysis. *Factors I and II* in [Table 28.10](#) represent common factors, since, on both of these factors, all six tests have loadings above zero, and at least three of the tests have substantial loadings on one of the two factors. In contrast to common factors are **specific factors**, which are factors that load on only one of the original variables that are employed in the factor analysis. Within the framework of factor analysis, specific factors generally account for only a small portion of the total variance, and typically do not play an important role in explaining the data. In addition to specific factors, another element that accounts for a small portion of the total variance are **error factors** (also referred to as **error variance**). Error factors represent uncontrolled variability — i.e., such things as poor reliability in measuring the variables, and/or other sources of error in the data that are beyond the control of the researcher.

Returning to our problem, the exact amount of the variance that can be accounted for by the two factors represented in [Table 28.10](#) can be obtained by adding up the numbers in the last row (labelled *Percent of Total Variance*) of the table. Thus: 44.21% + 35.71% = 79.92%. This tells us that 79.92% of the total variability in the data can be explained by the two factors, and that of that 79.92%, *Factor I* accounts for 44.21% of the variability, while *Factor II* accounts for the remaining 35.71% of the variability. In a factor analysis summary table, the first factor listed (identified as *Factor I*) will always account for the greatest amount of variability, followed by *Factor II* which will account for the next largest amount of variability, and so forth. If the results of the factor analysis were depicted in greater detail, and those additional factors that accounted for minimal variability were included in [Table 28.10](#), 100% of the variability would be accounted for. In any event, a factor analysis based on six initial variables in which two factors account for 79.92% of the variance, would be considered an excellent compromise between parsimony and comprehensiveness — i.e., one that explains most of the variability through use of a minimum number of factors.

At this point in the discussion, two other sets of values depicted in [Table 28.10](#) will be explained — specifically, **eigenvalues** and **communalities**. An **eigenvalue** is a numerical index that indicates the relative strength of each of the derived factors. On a more technical level, Kachigan (1986) notes that an eigenvalue (also known as a **latent root**) is the equivalent number of variables a factor represents. As an example, a factor with an eigenvalue of 4 accounts for as

much variance in the overall data as one would expect for four variables, if the total variability were evenly distributed among all of the variables. Thus the higher the eigenvalue associated with a factor, the larger the role that factor plays in explaining variability in the complete set of data. The value of an eigenvalue can range from any number above zero up to the number of variables being factor analyzed (which in our example is six). In order to employ an eigenvalue to determine the relative strength of a factor (in terms of percentage of variability that factor accounts for) one should do the following: a) Divide the value of the eigenvalue by the number of variables employed in the factor analysis; and b) Multiply the result of the division by 100. The resulting value will be the percentage of variability in the data that can be accounted for by that factor.

Thus, in our example: For *Factor I*: $2.6526 \div 6 = .4421$, and $.4421 \times 100 = 44.21\%$; For *Factor II*: $2.1424 \div 6 = .3571$, and $.3571 \times 100 = 35.71\%$. Note that the values 44.21% and 35.71% correspond to the values in the bottom row (labelled *Percent of Total Variance*) of [Table 28.10](#). A common rule employed by some researchers in factor analysis is to only employ factors that have an eigenvalue of 1 or greater (i.e., factors that at least account for the same amount of variance as one variable would be expected to). As a general rule, factors that have eigenvalues less than one will represent specific factors or error factors whose contribution in explaining the overall variability in the data is minimal.

The amount of the variance on any variable that can be explained by the derived common factors is referred to as **communality**. The communality of a variable is derived by squaring the factor loadings of the variable on each of the factors, and summing the squares. The sum of all the squared factor loadings on a variable represents the communality of that variable. Communality values, which (as previously noted) are listed in the last column of [Table 28.10](#), will always fall within the range 0 to 1. The communality for *Test A* is .9773 (97.73% when expressed as a percentage), since as noted previously: $(.98)^2 + (.13)^2 = .9773$. Thus, 97.73% of the variance on *Test A* can be explained by *Factors I* and *II*. Of the 100% total variance on *Test A*, only 2.27% (i.e., $100\% - 97.73\% = 2.27\%$) cannot be accounted for by either *Factor I* or *Factor II*. The remaining 2.27% of the variance may be explainable through other factors not depicted in [Table 28.10](#).

The following additional points with respect to the values depicted in [Table 28.10](#) should be noted: a) The sum of the communalities is equal to the sum of the eigenvalues. This will always be the case in a factor analysis summary table that has the same basic structure as [Table 28.10](#); b) If, in fact, all possible factors in a set of data, including specific factors and error factors are derived, and the squared factor loadings for each variable are summed, the communality of each variable will equal 1. In such a case the sum of the communalities of all the variables will always equal the total number of variables employed in the factor analysis; c) It is also the case that if all possible factors in a set of data are derived, the sum of the eigenvalues of all of the factors will equal the total number of variables; and d) For any given variable, the total variance on that variable can be attributed to the following: 1) The common variance between the variable and all the factors derived in the factor analysis for which the variable has a factor loading other than zero; 2) Error variance, which is obtained by subtracting the reliability coefficient of the variable from the value 1; and 3) Variance specific to the variable, which is computed by subtracting from the value 1, the total common variance (i.e., communality) of the variable on all common factors, and the error variance. The value that remains after this subtraction represents the specific variance unique to that variable. This specific variance is independent of all other variables.

Step 5 — Naming the factors: At the conclusion of a factor analysis, a researcher will generally assign a name to each of the factors. This is done by carefully examining the content of the variables (in this instance tests) that load high on a given factor. In our example, since

Factor I is essentially comprised of tests that measure *Anxiety (Test A)*, *Somatic Complaints (Test B)*, and *Guilt (Test C)*, one might elect to label *Factor I* **Neuroticism**. This might be the case, since many mental health professionals would include the behavior/traits measured by *Tests A, B, and C* as characteristic of a neurotic individual. Thus, someone who has high scores on these tests would be likely to be viewed as high on neuroticism, while a person with a low scorer on these tests would be viewed as low on neuroticism.

In the same respect, since *Factor II* is comprised of tests that measure *Friendliness (Test D)*, *Sensation Seeking (Test E)*, and *Dominance (Test F)*, one might elect to label *Factor II* **Extroversion**. This would be based on the premise that the behaviors/traits measured by *Tests D, E, and F* would be viewed by many psychologists as underlying components of the more general trait of extroversion.

Of course, one might challenge the above labels. For instance, one might, among other things, prefer to call *Factor I* **Mental Health** and *Factor II* **Energy Level**. The point to be made is that the naming of factors is based upon a subjective decision made by the researcher. It is conceivable, and not all that uncommon, that a name assigned to one or more factors by a researcher may be challenged by another researcher with respect to its appropriateness. Typically, in selecting a name for a factor, the larger the loading of a specific variable on that factor, the greater the role it should play in determining its name.

Additional comments on factor analysis A score, referred to as a **factor score**, can be derived for any subject on a given factor. A subject's factor score will be a composite score based on the relative contribution of all of the variables that represent that factor. Thus, a subject's score on each variable (i.e., personality test in the example under discussion) is weighted accordingly with respect to the degree that it measures that factor.

Since the sign of a factor loading is interpreted the same way as the sign of a correlation coefficient, the sign of a factor loading indicates the direction of the relationship between a subject's score on a variable and his or her score on that factor. Specifically, in the case of *Factor I*, the factor loading of .98 for *Test A* indicates that a subject who obtains a high score on *Test A* will have a high score on *Factor I*, and that a subject who has a low score on *Test A* will have a low score on *Factor I*. Just as positive factor loadings are interpreted as positive correlations, negative factor loadings are interpreted as negative correlations. Thus, if the factor loading for *Test A* was $-.98$, a subject who has a high score on *Test A* will have a low score on *Factor I*, and a subject who has a low score on *Test A* will have a high score on *Factor I*. If a factor loading for any variable is negative, the latter must be taken into account in determining a subject's score for that factor.

Diekhoff (1992), among others, notes that the issue of statistical significance in reference to factor analysis addresses the question of whether or not the obtained factor structure for a set of data is a reliable indicator of the factor structure in the underlying population. To be more specific, if it is determined that the factor structure is statistically significant, it would be expected that the same factor structure will be obtained if a factor analysis is conducted on another sample that is drawn from the same population from which the original sample was derived. Although a number of tests of statistical significance (all of which are mathematically complex and assume a relatively large sample size) have been developed for factor analysis, there is a lack of agreement among sources with respect to which test is most appropriate to employ. Some sources, however, use the following guidelines for determining whether or not a specific factor loading is statistically significant: a) For smaller sample sizes, any factor loading with an absolute value of .40 or greater is considered significant; and b) For larger sample sizes, any factor loading with an absolute value of .30 or greater is considered significant. (The reader should note that the amount of explainable variance on a variable attributable to a factor which has a loading of .30 is only $(.30)^2 = .09 = 9\%$ — certainly not a large amount by anyone's standards.).

Sources, however, do not agree on the values that constitute a “smaller” versus “larger” sample size.

If one employs the criterion of .30 for determining significance, [Table 28.10](#) reveals that *Tests A, B, and C* have significant loadings on *Factor I*, but not on *Factor II*, while *Tests D, E, and F* have significant loadings on *Factor II* but not on *Factor I*. This same information is, in part, revealed in [Table 28.9](#) by virtue of the following: a) *Tests A, B, and C* are highly correlated with one another; and b) *Tests D, E, and F* are highly correlated with one another. Although in our example the pattern of intercorrelations in [Table 28.9](#) suggests the underlying factorial structure of the data (i.e., that there are two primary factors, with one factor comprised of *Tests A, B, and C*, and the other factor comprised of *Tests D, E, and F*), such information will not always be obvious through inspection of a correlation matrix. To illustrate this point, if instead of six tests, the researcher had started out with 60 tests, it would be cumbersome (to say the least), and very likely impossible to discern the underlying factorial structure of the data by visual inspection of the correlation matrix. In any event, even if one is able to obtain a general picture of the factorial structure for a set of data, the information provided in [Table 28.10](#) provides more precise information than does the correlation matrix.

In actuality there are a number of different potential solutions that might result from the factor analysis of a set of data. A procedure referred to as **rotation** is regularly employed in factor analysis in order to arrive at what one considers to be the most useful solution. Since the factors that are derived in a factor analysis can be represented geometrically as well as mathematically, rotation is a procedure which involves rotating geometrical axes that serve as reference points for identifying the factors. It is up to the researcher to choose the degree of rotation which she believes will provide the best solution for the data.

Perhaps the most common practice in rotation is to configure the data so that each of the variables has a high loading on as few of the derived factors as possible (which, in fact, is the case in our example, since each test has a significant loading on only one of the factors). This type of rotation (which is employed within the framework of a procedure called the **simple structure**) is done in order to insure that one can come up with the most unambiguous and direct interpretation for each of the factors. To be more precise, Tabachnick and Fidell (1989, p. 637; 1996, p. 675) note that “if simple structure is present (and factors are not too highly correlated with one another), several variables correlate highly with each factor and only one factor correlates highly with each variable.” In an example such as ours in which each test only loads significantly on one factor, it is entirely possible that prior to rotation one or more of the tests had significant loadings on both *Factor I* and *Factor II*. It may have only been through the use of rotation that the data were reconfigured so that each test only had a significant loading on just one of the factors. A variable which has a high loading on only one factor (and thus, for the most part, only measures that factor) is called a **factorially simple variable**. On the other hand, a variable which has a high loading on more than one factor is referred to as a **factorially complex variable**.

Within the framework of factor analytic procedures, there are a variety of options one may employ with respect to the rotation of factors. Aside from the degree of rotation one employs, the most notable options involving rotation revolve around the issue of whether one wishes to derive **orthogonal** versus **oblique** factors. Orthogonal factors are independent factors — i.e., factors that have zero correlation with one another. Oblique factors, on the other hand, are factors which are not independent of one another — i.e., factors which are correlated with one another. Oblique factors can themselves be treated as variables, and factor analyzed into lower order factors. As a general rule, most factor analyses that are conducted involve the derivation of orthogonal rather than oblique factors.

The major criticisms directed toward factor analysis revolve around the subjective aspects of the procedure. As already noted, the type and degree of rotation employed by the researcher,

as well as the names one assigns to the derived factors, are based on subjective decisions. The criticism with respect to rotation is germane to the more general criticism that, within the framework of factor analysis, there are multiple procedures from which a researcher can choose, and the different procedures may not yield identical or even similar results. It is also important to realize that factor analysis will only provide useful information if it is employed with appropriate data. The variables a researcher initially elects to employ within the framework of a factor analysis must be carefully thought out in relation to the problem under study. If, due to prejudice or ignorance, a researcher ignores certain variables, the factor analysis will be unable to take such variables into account in describing the factorial structure of whatever it is that is ostensibly being studied. As Kachigan (1986, p. 400) notes, "Factor analysis does not create new information. It merely organizes, summarizes, and quantifies information that is fed into the system." In spite of the above noted criticisms, factor analysis is commonly employed by many researchers in multiple academic disciplines. Most researchers who have familiarity and experience with factor analysis would agree that when, used judiciously, it can be a powerful tool for evaluating a large body of data.

Canonical correlation **Canonical correlation** is a statistical procedure that correlates two sets of variables with one another. One set, which is comprised of two or more X variables, represents the predictor variables, while the other set, which is comprised of two or more Y variables, represents the criterion variables. Note that in contrast to **multiple regression**, which involves multiple predictor (X) variables and a single criterion (Y) variable, in **canonical correlation** there are multiple sets for both variables. The goal in **canonical correlation** is to identify pairs of linear combinations involving the two sets of variables that yield the highest correlation with one another. The term **canonical variate** is employed to identify any linear combination comprised of X (or Y) variables that is correlated with a linear combination of Y (or X) variables. The procedure in canonical correlation searches for the set of canonical variates that yields the maximum correlation coefficient. The next set of canonical variates (uncorrelated with the first) is then identified which yields the next highest correlation, and so on. Kachigan (1986) notes that canonical correlation is most likely to be useful in situations where there is doubt that a single variable in and of itself can serve as a suitable criterion variable. Consequently, by determining if a set of criterion variables correlate with a set of predictor variables, a clearer picture may emerge regarding the relationship between the dimensions represented by the X and Y variables. Tabachnick and Fidell (1996) note, however, that sometimes the statistical solution that results from a canonical analysis may prove difficult to interpret.

To illustrate canonical correlation, consider the following example. Let us assume a researcher has the following five lifestyle measures on a sample of subjects, which will represent the predictor (X) variables: Number of hours of exercise per week, number of grams of fat consumed per week, number of milligrams of caffeine consumed per week, number of grams of sugar consumed per week, and scores on a test assessing daily stress. In addition, the researcher has the following three scores as indices of health, which will represent the predictor (Y) variables: Diastolic blood pressure, body-fat ratio, and composite blood chemistry index of physical health. **Canonical correlation** can be employed to determine if there are reliable ways in which measures within the two sets of variables are related to one another. Thus, for example, one might find that a **canonical variate** comprised of two of the predictor variables (e.g., number of milligrams of caffeine consumed per week and number of grams of sugar consumed per week) is highly correlated with a **canonical variate** comprised of two criterion variables (e.g., diastolic blood pressure and composite blood chemistry index of physical health).

Like most multivariate procedures, the mathematics involved in conducting **canonical correlation** are quite complex, and for this reason it becomes laborious if not impractical to

implement without the aid of a computer. Since a full description of **canonical correlation** is beyond the scope of this book, the interested reader should consult sources such as Stevens (1986, 1996) and Tabachnick and Fidell (1989, 1996) which describe multivariate procedures in detail.

Discriminant analysis and logistic regression **Discriminant analysis** is a multivariate statistical procedure that derives equations which are designed to predict group membership (which represents the dependent/criterion variable) employing a set of quantitative measures (i.e., variables measured on an interval/ratio scale), which represent independent/predictor variables. The criterion variable in **discriminant analysis** is a discrete/qualitative variable that is comprised of two or more categories (e.g., breast cancer survivors versus breast cancer fatalities; religious affiliation, ethnic category, etc.). The equations derived in the analysis (which are called **discriminant functions**) are similar to those in regression analysis, in that in both procedures the equations are linear combinations of predictors that are correlated with a dependent variable.

Tabachnick and Fidell (1996) note that **discriminant analysis** addresses the same questions that are evaluated with the **multivariate analysis of variance (MANOVA)** (discussed in Section VII of the **single-factor between-subjects analysis of variance**). However, in the latter procedure, group membership serves as the independent variable, and the multiple quantitative measures represent the dependent variables. If within the context of **MANOVA** a significant difference is found between the groups, it reflects the fact that the dependent variables are reliable predictors of group membership.

To illustrate the application of **discriminant analysis**, assume a researcher wants to categorize people into one of two groups (which will represent the dependent/criterion variable) — those who have had a silent heart attack and those who have not. The categorization with respect to group would be based on equations that employ subjects' scores on the following four independent/predictor variables: cholesterol level, diastolic blood pressure, body fat ratio, and age. The equations derived in the discriminant analysis (i.e., the **discriminant functions**) will be linear combinations of the predictors that are correlated with the criterion variable.

An alternative to **discriminant analysis** for predicting group membership is **logistic regression**. As is the case with **discriminant analysis**, in **logistic regression** a discrete/qualitative criterion variable is employed. However, in **logistic regression** the independent/predictor variables can be discrete/categorical, continuous, or a combination of both. In addition, **logistic regression** is more flexible than **discriminant analysis**, since unlike the latter its reliability does not depend on certain restrictive normality assumptions regarding the underlying population distributions for the predictor variables. Like most multivariate procedures, the mathematics involved in conducting both **discriminant analysis** and **logistic regression** are quite complex, and for this reason they become laborious if not impractical to implement without the aid of a computer. Since a full description of the aforementioned procedures is beyond the scope of this book, the interested reader should consult sources such as Stevens (1996) and Tabachnick and Fidell (1996) that describe both procedures in detail. Kachigan (1986) provides an easily understandable nonmathematical discussion of discriminant analysis.

4. Meta-analysis and related topics **Meta-analysis** is methodology for pooling the results of multiple studies that evaluate the same general hypothesis. The purpose of meta-analysis is to allow a research community to come to some conclusion with respect to the validity of a hypothesis that is not based on one or two studies, but rather is based on a multitude of studies which have addressed the same general hypothesis. Hedges and Olkin (1985) note that R. A. Fisher (within the framework of the analyzing agricultural research) and Karl Pearson were among those who developed the first meta-analytic procedures in the 1930s. However, the work of Glass and his associates (Glass (1976, 1977) and Glass *et al.* (1981)) is largely responsible for

popularizing the use of meta-analysis within the scientific community. More recently, Robert Rosenthal and Donald Rubin have contributed to the development of many of the analytical techniques that are presently employed with the framework of meta-analysis.

Pooling the results of multiple studies that evaluate the same hypothesis is certainly not a simple and straightforward matter. More often than not there are differences between two or more studies which address the same general hypothesis. Rarely if ever are two studies identical with respect to the details of their methodology, the quality of their design, the soundness of execution, and the target populations that are evaluated. To further complicate matters, there is the issue of additional studies that may have evaluated the same hypothesis which were either never submitted for publication or were submitted but rejected. Rosenthal (1979, 1991, 1993) refers to this latter phenomenon (which will be discussed in detail later) as the **file-drawer problem**. In spite of the practical and theoretical difficulties involved in pooling the results of multiple studies, during the past 20 years numerous analytical procedures have been developed for this purpose.

Hedges and Olkin (1985) and Rosenthal (1991, 1993) note that two general approaches characterize meta-analytic research. One approach involves procedures that evaluate statistical significance for the combined results of multiple studies, while the second approach estimates treatment effects across studies. Hedges and Olkin (1985), Rosenthal (1991, 1993), and Wolf (1986) note that one method for evaluating the statistical significance of the combined results of multiple studies is the **vote-counting method**. The latter procedure involves identifying all of the studies that are believed to evaluate the same general hypothesis, and then determining the number of studies that yield a statistically significant result. The proportion of significant studies is then contrasted with the proportion of studies that are not significant (through use of a procedure such as the **binomial sign test for a single sample (Test 9)**). A variant of the vote-counting method statistically combines the probability values from two or more studies in order to compute a pooled probability value. Hedges and Olkin (1985) state that in spite of the intuitive appeal of such a simple and straightforward approach, the vote-counting procedure tends to be strongly biased toward the conclusion that there is no overall treatment effect for the variables under study. The latter bias is largely attributed to the relatively low power (due to the use of small sample sizes employed in studies in which a small to moderate effect size may be present) of research in certain disciplines such as the social and behavioral sciences. If one assumes low power, the vote-counting method will most likely only include as significant those studies in which the effect size is large, and fail to include studies where a weak or moderate effect size is present. Thus, the advantage of meta-analytic techniques which ignore the level of significance, but instead pool effect sizes, is that they circumvent the problem of low statistical power. Hedges and Olkin (1985) note that an optimal meta-analytic strategy should allow an investigator to compute an average treatment effect across all of the studies, as well as the consistency of the treatment effect across the studies. The general subject of treatment effects has been discussed throughout this book, often within the framework of the discussion of power. Specifically, various indices of treatment effect and measures of association (which are commonly employed as measures of treatment effect) are discussed in detail in Section VI of the following tests: The **single-sample t test**, the **t tests for two independent and dependent samples**, the **chi-square test for $r \times c$ tables**, and the tests that involve the **analysis of variance** procedures. Prior to describing a number of meta-analytic procedures, the subject of effect size will be discussed in greater detail.

Measures of effect size The discussion will begin by clarifying the relationship between statistical significance and effect size. Equation 28.76 is a general equation (presented by Rosenthal (1991, 1993) and discussed in Tatsuoka (1993)) which describes the relationship between effect size and a test statistic employed to measure statistical significance.

$$\text{Effect size} = \text{Significance test statistic} / \text{Sample size}$$

The *Effect size (ES)* value on the left side of Equation 28.76 can be any one of various measures of effect size discussed throughout this book. The value designated *Significance test statistic* will be the computed value for the inferential test statistic that is employed to determine statistical significance (e.g., a t , F , χ^2 , etc. value). The number employed to represent the *Sample size* will be some index that reflects the overall size of a sample employed in a study (but will usually not correspond exactly to the total number of subjects employed in a study). The relationship in Equation 28.76 reflects the fact that if sample size varies, in order for the effect size to remain unchanged, there must be a direct relationship between the magnitude of the computed test statistic and the sample size (i.e., as the value of the sample size increases, the magnitude of the test statistic must increase). This relationship was demonstrated earlier in reference to Example 16.1, which is employed to illustrate the **chi-square test for $r \times c$ tables**. In Section II of the latter test, Table 16.2 summarizes the data for Example 16.1. Analysis of the data in the latter table, which is comprised of 200 observations, yields a chi-square value of $\chi^2 = 18.18$. In Section VI of the **chi-square test for $r \times c$ tables** (under **measures of association for $r \times c$ contingency tables**), Table 16.22 summarizes the same experiment employing numbers (in the rows, columns, and cells of the summary table) that are half the value of those employed in Table 16.2. The number of observations in Table 16.22 is 100, and the computed test statistic is $\chi^2 = 9.1$. Since the identical degrees of freedom are employed in the analysis of both tables (i.e., $df = 1$, with $\chi^2_{.05} = 3.84$ and $\chi^2_{.01} = 6.63$), the level of significance represented by the p value obtained for Table 16.2 will be much lower than the p value obtained for Table 16.22. When Equation 28.76 is employed to compute the effect size index (*ES*) for Tables 16.2 and 16.22, the following values are obtained: $ES = 18.18/200 = .091$ (for Table 16.2) and $ES = 9.1/100 = .091$ (for Table 16.22). The aforementioned effect size values correspond to the square of the values that will be computed for the **phi coefficient** (ϕ) (computed with Equation 16.18) for each of the tables. Note that the chi-square values computed for the two tables are proportional to the sample sizes — in other words, the chi-square value computed for Table 16.2 is two times the chi-square value computed for Table 16.22, and the sample size employed in Table 16.2 is two times the size of the sample employed in Table 16.22. Yet, in spite of the latter, the identical effect size is computed for both tables. The fact that the two effect sizes are equal illustrates that unlike the computed value of a test statistic and its associated probability value, the effect size is independent of sample size. Thus, a computed test statistic (e.g., a t , F , χ^2 , etc. value) does not in itself provide information regarding the magnitude of a treatment effect. The reason for this is that the value of a test statistic is not only a function of the treatment effect, but is also a function of the size of the sample employed in an experiment. Since the power of a statistical test is directly related to sample size, the larger the sample the more likely a significant value will be obtained for the test statistic if there is an effect of any magnitude present in the underlying populations. Regardless of how small a treatment effect is present, the magnitude of the computed test statistic will increase as the size of the sample employed to detect it increases. Thus, it is impossible to determine from a significant test statistic and its associated p value (e.g., .05, .01, .001, etc.) whether the significant result is due to a large, medium, or small treatment effect.

The wisdom of using the conventional hypothesis testing model (which employs the result of a test of statistical significance) is addressed in detail at the end of the discussion of meta-analysis. For some time there has been controversy regarding the wisdom of employing tests of significance, insofar as the results of such tests are a function of power, which as noted previously is a function of sample size. The material to be presented on this issue later will describe an

alternative hypothesis testing model which some researchers believe should be employed in lieu of the conventional model. As you will see, regardless of which hypothesis testing model a researcher employs, the key to effective hypothesis testing ultimately boils down to using a representative sample that is large enough to detect any meaningful effect(s) present in the underlying population(s).

At this point a summary of the various indices that are employed to measure **effect size** will be presented. Throughout the discussion to follow, the terms **effect size** and **treatment effect** will be used interchangeably, since all of the measures described below are variously referred to as **measures of effect size**, **measures of magnitude of treatment effect**, **measures of association**, and **correlation coefficients**. All of these measures have been discussed previously in the book in reference to specific tests.

There are essentially two types of effect size indices. One type of index expresses effect size in the form of a correlation coefficient. This type of effect size index is computed at the conclusion of an experiment to indicate the proportion of variability on the dependent variable that can be attributed to the independent variable. Later in the discussion it will be illustrated that the summary value computed for an inferential test statistic (e.g., a t , F , χ^2 value) can be transformed into a correlation coefficient, in order that the latter can be employed as a measure of effect size for a set of data. An example of the latter (which can be found in the first section of this **Addendum**) is the computation of the **point-biserial correlation coefficient** to represent a measure of effect size for a t value.

A second type of effect size index is most commonly employed prior to conducting an experiment, in order to allow a researcher to determine the appropriate sample size to use to identify a hypothesized effect size. The latter type of index expresses effect size in terms of a difference score, which represents the difference (often in standard deviation units) between two underlying population parameters represented by two sample statistics, or the difference between a population parameter represented by a sample statistic and a hypothesized population parameter. Most of the effect size indices of this type were developed by Jacob Cohen, and are described in detail in his classic book on statistical power (Cohen (1977, 1988)). Since within the context of a meta-analysis there are times when a researcher may wish or be required to employ both types of effect size indices, equations are available for converting an effect size index based on a difference score into a correlational effect size index, and vice versa. Cohen (1977, 1988) describes the following effect size indices based on a difference score that are relevant to some of the inferential statistical tests discussed in this book: ***d***, ***f***, ***q***, ***g***, ***h***, and ***w***.³⁷ It should be noted that although some of the aforementioned indices can be employed to measure effect size in a study that involves two or more experimental conditions, as will be noted later in this section, meta-analysis is generally confined to evaluating hypotheses that contrast only two experimental conditions. A brief description of each of the effect size indices described by Cohen (1977, 1988) follows.

The *d* index The ***d* index** represents the difference between two means expressed in standard deviation units. The ***d* index** was previously employed in the computation of the power of the **single-sample *t* test** (where using Equation 2.5, $d = |\mu_1 - \mu|/\sigma$) and the ***t* tests for two independent and dependent samples** (where using Equations 11.10 and 17.14, $d = |\mu_1 - \mu_2|/\sigma$ and $d = |\mu_1 - \mu_2|/\sigma_D$). Cohen (1977; 1988, Ch. 2) has derived tables which allow a researcher to determine, through use of the ***d* index**, the appropriate sample size to employ if one wants to test a hypothesis about the difference between two means at a specified level of power. Cohen (1977; 1988, pp. 24–27) has proposed the following (admittedly arbitrary) ***d* values** as criteria for identifying the magnitude of an effect size: a) A **small effect size** is one that is greater than .2 but not more than .5 standard deviation units; b) A **medium effect size** is

one that is greater than .5 but not more than .8 standard deviation units; and c) A **large effect size** is greater than .8 standard deviation units. Equations 28.77 (Mullen and Rosenthal (1985), Rosenthal (1991, 1993) and 28.78 (Cohen (1977; 1988, p. 23) can be employed to convert an r value into a d value, and vice versa. Cohen (1977; 1988, pp. 23-27) states that the r value computed with Equation 28.78 is a **point-biserial correlation** (r_{pb}) when $p_0 = p_1$. When $p_0 \neq p_1$, Equation 28.78 becomes $r = d/\sqrt{d^2 + (1/p_0p_1)}$.³⁸

$$d = \sqrt{\frac{4r^2}{1 - r^2}} \quad (\text{Equation 28.77})$$

$$r = \frac{d}{\sqrt{d^2 + 4}} \quad (\text{Equation 28.78})$$

Tatsuoka (1993) notes that Glass (1976) has developed a sample analogue of **Cohen's d index**, which is designed to serve as a measure of association when a researcher has an experimental group and a control group. Equation 28.79 is employed to compute **Glass's g index**.

$$g = \frac{\bar{X}_e - \bar{X}_c}{\hat{s}_c} \quad (\text{Equation 28.79})$$

In Equation 28.79, \bar{X}_e and \bar{X}_c , respectively, represent the means of the experimental and control groups, and \hat{s}_c represents the estimated population standard deviation of the control group. Note that Glass (1976) employs the standard deviation of the control group rather than a pooled standard deviation involving both groups in the denominator of his equation. He does this since he believes that if pooled variability is employed in the denominator of the equation, the relevant g value for a specific experimental group and a control group will be unduly influenced by the variability of other experimental groups which are not involved in the comparison. A more detailed discussion of **Glass's g index** can be found in Tatsuoka (1993).

The f index The **f index** is a generalization of the **d index** to the case where there are three or more means. The **f index** was previously discussed in Section VI of the **single-factor between-subjects analysis of variance**. Cohen (1977; 1988, Ch. 8) has derived tables that allow a researcher to determine, through use of the **f index**, the appropriate sample size to employ if one wants to test a hypothesis about the difference between three or more means at a specified level of power. Cohen (1977; 1988, pp. 284-288) has proposed the following (admittedly arbitrary) f values as criteria for identifying the magnitude of an effect size: a) A **small effect size** is one that is greater than .1 but not more than .25; b) A **medium effect size** is one that is greater than .25 but not more than .4; and c) A **large effect size** is greater than .4.

Tatsuoka (1993) notes that Hedges (1981) has developed the g' index as an alternative to the **f index**. As is the case with the latter index, g' is designed to be used as a measure of effect size for the analysis of variance. **Hedges' g'** is computed with Equation 28.80.

$$g' = \frac{\bar{X}_{e_j} - \bar{X}_c}{\sqrt{MS_{WG}}} \quad (\text{Equation 28.80})$$

In Equation 28.80, \bar{X}_{e_j} represents the mean of the j^{th} group and \bar{X}_c represents the mean

of the control group. $\sqrt{MS_{WG}}$ is the square root of the pooled estimate of within-groups variability employed in the analysis of variance. A more detailed discussion of **Hedges' g' index** can be found in Tatsuoka (1993).

The q index The **q index** represents the difference between two Pearson product-moment correlation coefficients, where the latter values are expressed through use of **Fisher's z_r transformation**. The equation for the **q index** is $q = z_1 - z_2$, where z_1 and z_2 are the Fisher transformed z_r values for the two correlation coefficients. Cohen (1977; 1988, Ch. 4) has derived tables that allow a researcher to determine, through use of the **q index**, the appropriate sample size to employ if one wants to test a hypothesis about the difference between two correlation coefficients at a specified level of power. Cohen (1977; 1988, pp. 113–116) has proposed the following (admittedly arbitrary) **q** values as criteria for identifying the magnitude of an effect size: a) A **small effect size** is one that is greater than .1 but not more than .3; b) A **medium effect size** is one that is greater than .3 but not more than .5; and c) A **large effect size** is greater than .5.

The g index The **g index** (not to be confused with **Glass's g index** discussed earlier) can be employed to compute the power of the **binomial sign test for a single sample**. The **g index** represents the distance in units of proportion from the value .50. The equation Cohen (1977, 1988) employs for the **g index** is $g = P - .50$, where P represents the hypothesized value of the population proportion stated in the alternative hypothesis — in this instance it is assumed that the researcher has stated a specific value in the alternative hypothesis as an alternative to the value that is stipulated in the null hypothesis. Cohen (1977; 1988, Ch. 5) has derived tables that allow a researcher, through use of the **g index**, to determine the appropriate sample size to employ if one wants to test a hypothesis about the distance of a proportion from the value .5 at a specified level of power. Cohen (1977; 1988, pp. 147–150) has proposed the following (admittedly arbitrary) **g** values as criteria for identifying the magnitude of an effect size: a) A **small effect size** is one that is greater than .05 but not more than .15; b) A **medium effect size** is one that is greater than .15 but not more than .25; and c) A **large effect size** is greater than .25.

The h index The **h index** can be employed to compute the power of the **z test for two independent proportions (Test 16d)**. The value h is an effect size index reflecting the difference between two population proportions. h is computed through use of the arcsine transformation (discussed in Section VII of the **t test for two independent samples**). The equation for the **h index** is $h = \phi_1 - \phi_2$ (where ϕ_1 and ϕ_2 are the arcsine transformed values for the proportions). Cohen (1977; 1988, Ch. 6) has derived tables that allow a researcher, through use of the **h index**, to determine the appropriate sample size to employ if one wants to test a hypothesis about the difference between two population proportions at a specified level of power. Cohen (1977; 1988, pp. 184–185) has proposed the following (admittedly arbitrary) **h** values as criteria for identifying the magnitude of an effect size: a) A **small effect size** is one that is greater than .2 but not more than .5; b) A **medium effect size** is one that is greater than .5 but not more than .8; and c) A **large effect size** is greater than .8.

The w index The **w index** can be employed to compute the power of the **chi-square goodness-of-fit test (Test 8)** and the **chi-square test for $r \times c$ tables**. The value w is an effect size index reflecting the difference between expected and observed frequencies. The equation for the **w index** is $w = \sqrt{\sum[(P_{alt} - P_{null})^2/P_{null}]}$. The latter equation indicates the following: a) For each of the cells in the chi-square table, the proportion of cases hypothesized in the null hypothesis is subtracted from the proportion of cases hypothesized in the alternative hypothesis;

b) The obtained difference in each cell is squared, and then divided by the proportion hypothesized in the null hypothesis for that cell; c) All of the values obtained for the cells in part b) are summed; and d) w represents the square root of the sum obtained in part c). Cohen (1977; 1988, Ch. 7) has derived tables that allow a researcher to determine, through use of the **w index**, the appropriate sample size to employ if one wants to test a hypothesis about the difference between observed and expected frequencies in a chi-square table at a specified level of power. Cohen (1977; 1988, pp. 224–226) has proposed the following (admittedly arbitrary) w values as criteria for identifying the magnitude of an effect size: a) A **small effect size** is one that is greater than .1 but not more than .3; b) A **medium effect size** is one that is greater than .3 but not more than .5; and c) A **large effect size** is greater than .5.

With the exception of **Glass's g** and **Hedges' g'** , the effect size indices discussed above are typically employed for power computations prior to conducting an inferential statistical test.³⁹ Consequently, it is far more common that the effect size indices employed within the framework of meta-analysis are correlational measures (an r value) that are based on the empirical data obtained in a study. At this point the use of the **Pearson product-moment correlation coefficient** as a measure of effect size will be discussed.

Pearson r as a measure of effect size Although outside of the context of meta-analysis r^2 (the **coefficient of determination** which is discussed in Section V) rather than r is more commonly used to represent the measure of effect size, either of the values can be employed for this purpose. In discussing the use of the **Pearson product-moment correlation coefficient** as a measure of effect size, Cohen (1977; 1988, pp. 78–81) has proposed the following (admittedly arbitrary) r values as criteria for identifying the magnitude of an effect size: a) A **small effect size** is one that is greater than .1 but not more than .3; b) A **medium effect size** is one that is greater than .3 but not more than .5; and c) A **large effect size** is greater than .5. As previously noted in Section VI, Cohen (1977; 1988, Ch. 3) has derived tables for computing power that allow a researcher to determine the appropriate sample size to employ if one wants to evaluate an alternative hypothesis that designates a specific value for a population correlation (when the null hypothesis is $H_0: \rho = 0$). In addition to **Pearson r** , Rosenthal (1993) notes that any of the following measures of association (all of which are special cases of the **Pearson product-moment correlation coefficient**) can be used to represent an r value within the framework of a meta-analysis: a) The **point-biserial correlation coefficient** (discussed earlier in this **Addendum**), which is employed as a measure of association for the **t test for two independent samples** (and can also be employed as a measure of association for the **t test for two dependent samples (Test 17)**); b) The **phi coefficient** (ϕ) (which is discussed in Section VII as well as in Section VI of the **chi-square test for $r \times c$ tables**), which is employed when both variables are dichotomous; c) **Spearman's rank-order correlation coefficient**, which is employed when both variables are in a rank-order format. In Section VI of **Spearman's rank-order correlation coefficient**, it is demonstrated that the latter correlation coefficient is a special case of the **Pearson product-moment correlation coefficient**.

Meta-analytic procedures⁴⁰ Rosenthal (1991, 1993) describes the following four types of meta-analytic procedures (as well as additional procedures that will not be covered): a) Procedures that compare two or more studies with respect to significance level. In the case of two studies, these procedures determine whether or not the p values obtained for two studies are significantly different from one another. In the case of three or more studies, the meta-analytic procedures determine whether the p values for the k studies (where k represents the number of studies) are homogeneous — i.e., consistent with one another; b) Procedures that combine the significance levels (i.e., p values) of two or more studies, and obtain a combined/pooled estimate

of the p value for all k studies; c) Procedures that compare two or more studies with respect to effect size. In the case of two studies, these procedures determine whether or not the computed values for the effect sizes of the two studies are significantly different from one another. In the case of three or more studies, the meta-analytic procedures determine whether the computed values for the effect sizes of the k studies are homogeneous — i.e., consistent with one another; and d) Procedures that combine the effect size values computed for two or more studies, and obtain a combined/pooled estimate of effect size for all k studies.

It should be noted that when the results of two or more studies are compared or combined within the framework of a meta-analysis, it is assumed that the k studies are independent of one another (i.e., represent separate studies employing different subjects). To carry out the procedures to be described in this section, it is required that the test statistic representing the outcome of each of the k studies is standardized (i.e., that the result of each study is summarized by the same test statistic). The most common statistics employed for this purpose are values of z and r . In meta-analytic procedures that compare or combine significance levels, p values are converted into z values. In procedures that compare or combine effect sizes, the effect size is commonly expressed as an r value. At this point I will summarize a number of equations (described in Rosenthal (1985, 1991, 1993)) that allow a researcher to convert the results of an inferential statistical test into an r value.

a) Within the framework of conducting a **t test for two independent samples** or a **t test for two dependent samples**, Equation 28.81 can be employed to transform a t value into an r value.

$$r = \sqrt{\frac{t^2}{t^2 + df}} \quad \text{(Equation 28.81)}$$

The value computed with Equation 28.81 is the square root of the value computed with Equation 28.45 (the equation for computing **eta squared** (η^2), which is equivalent to the square of the **point-biserial correlation** (r_{pb})). It should also be noted that within the framework of conducting a **t test**, Equation 28.78 was presented earlier for conversion of **Cohen's d index** into an r value.⁴¹

b) Within the framework of conducting an **analysis of variance** where the degrees of freedom for the numerator equals 1 (i.e., two groups/conditions), Equation 28.82 can be employed to transform an F value into an r value.

$$r = \frac{F}{F + df_{\text{error}}} \quad \text{(Equation 28.82)}$$

c) Within the framework of conducting a **chi-square test for $r \times c$ tables**, where $df = 1$ (i.e., a 2×2 contingency table), Equation 28.83 can be employed to transform a chi-square value into an r value.

$$r = \sqrt{\frac{\chi^2}{n}} \quad \text{(Equation 28.83)}$$

Note that Equation 28.83 is the same as Equation 16.18, which is employed to compute the **phi coefficient** (ϕ).

d) If a researcher wants to transform a z value into an r value, Equation 28.84 can be employed.

$$r = \sqrt{\frac{z^2}{n}} \quad \text{(Equation 28.84)}$$

Rosenthal (1991, 1993) notes that within the context of meta-analysis, he is only interested in **single degree of freedom** comparisons — which is the term he uses to refer to studies that compare two groups/conditions with one another. He states that meta-analytic procedures are of little use when $df > 1$, since, when an omnibus test (e.g., an analysis of variance, chi-square test, etc.) compares more than two groups, it becomes difficult or impossible to answer the questions addressed by meta-analysis with a high degree of precision. In other words, an omnibus test statistic based on more than two experimental conditions does not identify which of the conditions are significantly different from other another. The use of the term **single degree of freedom comparison** within the context of a two group/condition experiment refer to the following: a) When there are two groups/conditions, the between-groups/between-conditions degrees of freedom for the **analysis of variance** is equal to 1. When $df_{BG/BC} = 1$, the **analysis of variance** and the **t tests for two independent and dependent samples** are equivalent procedures; and b) In the case of the **chi-square test for $r \times c$ tables**, $df = 1$ when two groups are contrasted with one another.

Demonstration of meta-analytic procedures In this section the following four meta-analytic procedures described by Rosenthal (1985, 1991, 1993) will be presented: a) A procedure for comparing k studies with respect to homogeneity of significance level; b) A procedure for obtaining a combined significance level (p value) for k studies; c) A procedure for comparing k studies with respect to homogeneity of effect size; and d) A procedure for obtaining a combined effect size for k studies.

Example 28.7 will be employed to demonstrate aforementioned meta-analytic procedures.

Example 28.7 *Five independent studies (to be identified by the letters A, B, C, D, and E) evaluating the same general hypothesis (e.g., patients who receive a specific type of therapy will do better than a no-treatment control group) are conducted over a two year period. All of the studies employ an independent groups design with an independent variable comprised of two levels. The analysis of the data in each of the studies involved the use of the t test for two independent samples to determine if there was a difference between the means of an experimental and control group. In addition, a point-biserial correlation (which will be represented by the notation r) was computed for each study, to determine the magnitude of any effect size that was present. In studies A, B, C, and D the mean score of the experimental group was higher than the mean score of the control group. The one-tailed probability values (based on the result of the t-test) and the point-biserial correlations computed for the studies follow: A ($p = .05$; $r = .60$); B ($p = .01$; $r = .50$), C ($p = .10$; $r = .20$), D ($p = .20$; $r = .30$). The result of study E was in the opposite direction of the other four studies — i.e., the mean of the control group was higher than the mean of the experimental group. The one-tailed probability value (based on the result of the t-test) and the point-biserial correlation for study E follow: E ($p = .09$; $r = .15$). The total number of subjects employed in each of the studies were: A(20); B(40); C(10); D(30); E(25). Compare the p values and effect sizes with respect to homogeneity, and compute a combined/pooled p value and effect size for the five studies.*

At this point it should be stated that all probability values (p) used within the framework of the meta-analytical procedures to be described will be **one-tailed**. The reason for this is that we want to be able to designate the direction of the outcome of each study — i.e., whether the mean of the experimental group is larger than the mean of the control group, or vice versa. Thus, the

left tail of the distribution will represent one directional outcome and the right tail the other directional outcome. Numerically, the direction of an outcome will be designated in reference to a summary statistic (e.g., an r or z value) by assigning a plus sign to outcomes in one tail of the sampling distribution, and a minus sign to outcomes in the other tail.

Test 28n: Procedure for comparing k studies with respect to significance level The procedure to be described in this section evaluates the following null and alternative hypotheses.

Null hypothesis H_0 : The p values obtained for the k studies are consistent/homogenous with one another.

Alternative hypothesis H_1 : The p values obtained for the k studies are not consistent/homogenous with one another.

Equation 28.85 can be employed to evaluate whether k (where $k \geq 2$) probability (p) values are homogeneous (i.e., consistent with one another). When the test to be described is employed with $k = 2$ studies, it simply evaluates whether there is a significant difference between the two p values.

$$\chi^2 = \sum_{j=1}^k (z_j - \bar{z}_k)^2 \quad \text{(Equation 28.85)}$$

Where: \bar{z}_k represents the average z value computed for the k published studies
 z_j represents the z value for the j^{th} study

In order to employ Equation 28.85, it is required that each of the p values is converted into its corresponding standard normal deviate (i.e., a z value). In order to do the latter, we find the p value in **Column 3** of **Table A1** in the **Appendix** which corresponds to the p value obtained for a given study (note that the p values in **Column 3** represent one-tailed probabilities). The z value in the same row (i.e., the value in **Column 1**) of **Table A1** that corresponds to the latter p value is employed as its standard normal deviate. Thus, in the case of *Study A*, which has a p value of .05, the value $z = 1.65$ is employed to represent it, since the probability/proportion in **Column 3** of **Table A1** is .0495 (which is the closest value to .05). In the case of *Study B*, which has a p value of .01, the value $z = 2.33$ is employed to represent it, since the probability/proportion in **Column 3** of **Table A1** is .0099 (which is the closest value to .01). Employing the same methodology with *Studies C* and *D*, we find that the z values which correspond to the p values .10 and .20 are 1.28 and .84. In the case of *Study E*, the z value that corresponds to the p value .09 is 1.34. The z values for *Studies A, B, C, and D* (the outcomes of which are in the same direction) will all be assigned a positive sign. The z value for *Study E* (the outcome of which is in the opposite direction of the other studies) will be assigned a negative sign.⁴² Thus, the five z values we will employ in Equation 28.85 are 1.65, 2.33, 1.28, .84, and -1.34.

The following protocol is employed for Equation 28.85: a) Compute the mean of the k z_j values; b) Subtract the mean from each of the k z_j values, and square each difference score; and c) Compute the sum of the k squared difference scores. The resulting value, which is a chi-square value, represents the test statistic, for which the degrees of freedom are $df = k - 1$.

We compute the average of the five z values to be $\bar{z}_k = .95$. When the latter value along with the five z scores that are computed above are substituted in Equation 28.85, we obtain the value $\chi^2 = 7.75$.

$$\chi^2 = (1.65 - .95)^2 + (2.33 - .95)^2 + (1.28 - .95)^2 + (.84 - .95)^2 + (-1.34 - .95)^2 = 7.75$$

Since there are 5 studies, $df = 5 - 1 = 4$. Employing [Table A4](#) in the **Appendix**, for $df = 4$, $\chi^2_{.05} = 9.49$ and $\chi^2_{.01} = 13.28$ (the probabilities for these critical values are one-tailed). In order to reject the null hypothesis, the computed chi-square value must be equal to or greater than the tabled critical value at the prespecified level of significance. Since the obtained value $\chi^2 = 7.75$ is less than $\chi^2_{.05} = 9.49$, the null hypothesis is retained. In other words, the data do not indicate that the probability values obtained for the five studies are inconsistent (i.e., not homogeneous) with one another.

Test 28o: The Stouffer procedure for obtaining a combined significance level (p value) for k studies A number of procedures have been developed for obtaining a combined/pooled p value for k independent studies that evaluate the same general hypothesis. These procedures are relevant for obtaining a combined probability for studies that involve a directional hypothesis testing situation where $df = 1$ (i.e., a study in which two groups/conditions are contrasted with one another). Birnbaum (1954) and Rosenthal (1978, 1991) provide a good overview of the various procedures. The specific test to be described here, which was developed by Stouffer *et al.* (1949), computes a combined p value through use of Equation 28.86. Sources that discuss this test in greater detail are Conover (1999), Mosteller and Bush (1954), Rosenthal (1991, 1993), and Wolf (1986).⁴³

$$z = \frac{\sum_{j=1}^k z_j}{\sqrt{k}} \quad \text{(Equation 28.86)}$$

Where: z_j represents the z value for the j^{th} study

As is the case with Equation 28.85 (employed for **Test 28n**), Equation 28.86 requires that we convert each of the p values obtained for the k studies into its corresponding standard normal deviate (i.e., a z score). Once again it should be emphasized that one-tailed probabilities are always employed. Since we have already computed the appropriate z values for **Test 28n**, we are ready to employ Equation 28.86. The protocol for the equation requires that we sum the k z_j values, and divide the sum by the square root of k . The resulting z value represents the test statistic, which is evaluated with [Table A1](#).

When the z scores for Example 28.7 that correspond to the probability values obtained for the $k = 5$ studies are substituted in Equation 28.86, we obtain $z = 2.13$.

$$z = \frac{1.65 + 2.33 + 1.28 + .84 + (-1.34)}{\sqrt{5}} = \frac{4.76}{\sqrt{5}} = 2.13$$

Employing [Table A1](#), we determine that the one-tailed probability associated with $z = 2.13$ is .0166. The latter value represents the combined probability for the five studies. Since $p = .0166$ is less than $p = .05$, the combined probability derived from the test is statistically significant.⁴⁴ The combined probability value of .0166 is an overall probability in favor of the outcome of the majority of the studies (in which the experimental group obtained a higher mean than the control group). It is important to note that in Example 28.7, the outcomes of the five studies (reflected by the five p values) appear to be reasonably consistent (although some might consider the contrary outcome of *Study E* to be somewhat problematical). As will be noted later, when Equation 28.86 yields a combined probability value that is significant, yet the outcomes of the studies are not homogeneous, the obtained combined probability must be viewed with great caution.

The file drawer problem Rosenthal (1979) employs the term **file drawer problem** to refer to the fact that there may be additional studies which evaluated the same hypothesis evaluated in a meta-analysis, yet were never submitted for publication or were submitted but rejected. Consequently, if one computes a statistically significant combined probability value for k studies with Equation 28.86, the following question might be asked: If, in fact, the null hypothesis is true, how many additional **null studies** would have to be conducted in order to render the combined probability value nonsignificant? A **null study** is one in which there is no difference between the two groups and, consequently, the values $z = 0$ and $p = .50$ will be obtained. Rosenthal (1979) derived Equation 28.87 from Equation 28.86 to answer the latter question. Equation 28.87 calculates the number of studies averaging null results that must be in the file drawer in order to increase the Type I error rate (i.e., combined p value) so that it equals a specific value (typically 5% or greater).

$$X = \frac{k}{z_{\alpha}^2} (k\bar{z}_k^2 - z_{\alpha}^2) \quad (\text{Equation 28.87})$$

Where: X represents the number of additional studies that are required to render the combined probability nonsignificant
 z_{α} represents the critical one-tailed z value at the required level of statistical significance for the combined probability
 \bar{z}_k represents the average z value computed for the k published studies

Rosenthal (1979) notes that if we employ the .05 level of significance, the one-tailed value $z_{.05} = 1.645$ (which for purposes of greater precision is used rather than the usual $z = 1.65$) is employed to represent z_{α} in Equation 28.87. When $z_{\alpha} = 1.645$ is substituted in the latter equation, it becomes Equation 28.88.

$$X = \frac{k}{2.706} (k\bar{z}_k^2 - 2.706) \quad (\text{Equation 28.88})$$

By employing Equation 28.88 one can determine how many additional null studies will be required in order for the combined p value for a hypothesis under study to equal .05. One additional null study above the computed value of X will render the combined probability above .05, and thus the combined probability for the general hypothesis will no longer be statistically significant. In the case of Example 28.7, if we substitute the values $k = 5$ and $\bar{z}_k = .95$ in Equation 28.88, we compute the value $X = 3.34$.

$$X = \frac{5}{2.706} [(5)(.95)^2 - 2.706] = 3.34$$

This result tells us that only four additional null studies evaluating the same general hypothesis are required to be in the **file drawer** to produce a nonsignificant combined probability (since 4 is the next integer number above the obtained value $X = 3.34$). If the results of four such studies are combined with the five studies documented in Example 28.7, the resulting probability computed with Equation 28.86 will be greater than .05. Specifically, if four p values of .50 and their corresponding z values of zero are added to Example 28.7, Equation 28.86 will yield the value $z = 1.59$, which is less than the tabled critical .05 value $z_{.05} = 1.65$. Note that the sum of the z values, which equals 4.76, does not change when $k = 9$ (which represents the original five studies plus the four null studies), since $z = 0$ for each of the four additional studies. Thus:

$z = 4.76/\sqrt{9} = 1.59$. Rosenthal (1991, 1993) has addressed the question of how one might go about estimating the number of unpublished studies that remain in the file drawer. He suggests a conservative estimate of the upper limit of the number of unpublished studies might be approximated by the value $5k + 10$ (e.g., if $k = 5$, the minimum estimate for the number of studies in the file drawer will be $(5)(5) + 10 = 35$).

The file drawer problem is most commonly discussed within the context of highly significant meta-analytic research — in other words, in instances where the combined probability for a hypothesis is at a statistically significant level, with the value of p being very low. In such an instance, a skeptic would want to rule out the likelihood that the null hypothesis is, in fact, true, and that many of the published studies, in reality, represent Type I errors (i.e., spuriously significant results). Since there is a bias toward publishing (as well as submitting) significant results, it is sometimes suggested that if all the unpublished studies in the file drawer were taken into account, support for many a hypothesis would evaporate. Rosenthal (1991) discusses the latter issue, as well as empirical studies that address the question of how publication bias can influence the results of a meta-analysis.

At this point in the discussion, it is worth noting that it is possible to have a set of k studies and obtain a significant result for **Test 28n**, and also obtain a significant combined probability value for **Test 28o**. As an example, let us assume that the outcomes of the five studies in Example 28.7 were such that three favored the experimental group and two favored the control group (in terms of which group obtained the higher mean). Let us also assume the following: a) The p values for the three studies which favored the experimental group are quite low (e.g., in the .001 range); and b) In the case of the other two studies, the results of both are significant at the .05 level in favor of the control group.

It is likely that if **Test 28n** is employed to evaluate the probabilities for the aforementioned five studies, we will conclude that the results of the studies are not homogeneous (i.e., a significant chi-square value will be computed with Equation 28.85). Nevertheless, it is conceivable that when the five probabilities are evaluated with **Test 28o**, a combined p value below .05 (in favor of the experimental group) will be obtained. Under such circumstances the combined probability value would have to be viewed with even greater caution than the combined probability of $p = .0166$, which was obtained through use of Equation 28.86 for Example 28.7. This is the case, since if all five studies are statistically significant, but three are in one direction and two are in the opposite direction, the consistency of the outcomes of the five studies leaves a lot to be desired. The lack of consistency in the probability values can be the result of any of the following: a) Differential effect sizes being present in the k studies; b) Differences in the size of the samples employed (which influence the power of each of the k tests); c) Differences in methodology; d) Errors in instrumentation or recording; e) Faulty data analysis; or f) Some combination of one or more of the aforementioned factors. In the discussion to follow, it will be emphasized that in order for a statistically significant combined probability value to be meaningful, there should be sufficient evidence it reflects the fact that the k studies employed in a meta-analysis yielded relatively homogenous results. The studies should not only exhibit consistency with regard to the direction of their outcome, but more importantly should exhibit consistency with respect to the magnitude of the effect size present in the k studies.

Neither of the two analyses conducted up to this point (i.e., **Tests 28n** and **28o**) provide us with any information regarding effect size for Example 28.7. Before proceeding, it is important to reiterate that the p value obtained for any study is always a direct function of the power of the statistical test, and power is a direct function of the sample size employed in a study. In order to reject the null hypothesis if a small (or even modest medium) effect size is present, it will be required that the researcher employ a large sample size. To illustrate this point, assume that two studies are conducted involving two independent samples which evaluate the same hypothesis.

Let us also assume that in the underlying populations a small effect size characterizes the relationship between the independent and dependent variables. One study (*A*) employs a large sample size, while the other study (*B*) employs a relatively small sample size. In the case of *Study A*, it is very likely that we will be able to reject the null hypothesis, and the larger the sample size the lower the p value that will be obtained for that study. In the case of *Study B*, we will probably not be able to reject the null hypothesis, since the small sample size will severely compromise the power of the test — i.e., the test's ability to detect a difference between the groups. The computed p value for *Study B* will most likely be above .05, and, in fact, may be considerably larger. Yet if we compute the effect size for both studies, we obtain the same value. Let us assume that latter value is computed to be $r = .15$, which by Cohen's (1977, 1988) standards constitutes a small effect size. Let us also assume that additional studies of the same hypothesis consistently obtain approximately the same effect size, but only a few of them — specifically, those which happen to employ a large sample size — yield significant results. Obviously, such an occurrence provides support for Hedges' (1995) and Rosenthal's (1991, 1993) contention, that within the framework of meta-analysis, it is more prudent to compare and/or combine effect sizes than it is to compare and/or combine p values. The next two procedures to be presented are designed to do just that.

Test 28p: Procedure for comparing k studies with respect to effect size The procedure to be described in this section evaluates the following null and alternative hypotheses.

Null hypothesis H_0 : The effect size values obtained for the k studies are consistent/homogenous with one another.

Alternative hypothesis H_1 : The effect size values obtained for the k studies are not consistent/homogenous with one another.

Equation 28.89 can be employed to evaluate whether k (where $k \geq 2$) effect size values (as measured by r) are homogeneous (i.e., consistent with one another). (Equation 28.24 in Section VI is a different but equivalent version of Equation 28.89.) When the test to be described is employed with $k = 2$ studies, it simply evaluates whether there is a significant difference between the two effect size values.

$$\chi^2 = \sum_{j=1}^k (n_j - 3)(z_{r_j} - \bar{z}_{r_k})^2 \quad \text{(Equation 28.89)}$$

Where: z_{r_j} represents the Fisher transformed z_r value for the j^{th} study
 \bar{z}_{r_k} represents the average Fisher transformed z_r value computed for the k published studies. It is a weighted average, since the sample size of each study is taken into account. The value of \bar{z}_{r_k} is computed with Equation 28.25.
 n_j represents the sample size in the j^{th} study

In order to employ Equation 28.89 (or Equation 28.24), it is required that the r value for each study (which, as noted earlier, is used to represent the magnitude of effect size) is converted into a corresponding **Fisher tranformed value** (discussed in Section VI). The latter is accomplished through use of either Equation 28.18 or [Table A17](#). Employing [Table A17](#), the Fisher transformed z_r values for the five studies are as follows.

$$z_{r_A} = .693 \quad z_{r_B} = .549 \quad z_{r_C} = .203 \quad z_{r_D} = .310 \quad z_{r_E} = .151$$

We will assign the Fisher transformed z_r values for *Studies A, B, C, and D* a positive sign, since they are all in the direction that favors the experimental group. Since the outcome of *Study E* is in the opposite direction, it is assigned a negative sign. Thus, for *Study E* we will use the value $z_{r_E} = -.151$.⁴⁵

Employing Equation 28.25, the average of the five Fisher transformed z_r values is computed to be $z_{r_k} = .351$.

$$\begin{aligned}\bar{z}_{r_k} &= \frac{\sum_{j=1}^k (n_j - 3) z_{r_j}}{\sum_{j=1}^k (n_j - 3)} \\ &= \frac{(20-3)(.693) + (40-3)(.549) + (10-3)(.203) + (30-3)(.310) + (25-3)(-.151)}{(20-3) + (40-3) + (10-3) + (30-3) + (25-3)} \\ &= \bar{z}_{r_k} = .351\end{aligned}$$

We are now ready to substitute the appropriate values in Equation 28.89. The following protocol is employed in using the latter equation: a) For each of the k studies, subtract the average Fisher transformed z_r value (i.e., $z_{r_k} = .351$) from the Fisher transformed z_r value for that study. Square the difference score, and multiply that value by the total sample size less three; and b) The sum of the k values computed in part a) is a chi-square value, which represents the test statistic. The degrees of freedom employed in evaluating the chi-square value are $df = k - 1$. The computations employing Equation 28.89 are shown below, which yield the value $\chi^2 = 9.18$.

$$\begin{aligned}\chi^2 &= (20 - 3)(.693 - .351)^2 + (40 - 3)(.549 - .351)^2 + (10 - 3)(.203 - .351)^2 \\ &\quad + (30 - 3)(.310 - .351)^2 + (25 - 3)(-.151 - .351)^2 = 9.18\end{aligned}$$

Since there are 5 studies, $df = 5 - 1 = 4$. Employing [Table A4](#), for $df = 4$, $\chi^2_{.05} = 9.49$ and $\chi^2_{.01} = 13.28$ (the probabilities for these critical values are one-tailed). In order to reject the null hypothesis, the computed chi-square value must be equal to or greater than the tabled critical value at the prespecified level of significance. Since the obtained value $\chi^2 = 9.18$ is less (albeit barely) than $\chi^2_{.05} = 9.49$, the null hypothesis is retained. In other words, the data do not indicate that the effect sizes obtained for the five studies are inconsistent with one another. Realistically, however, since the outcome is so close to being significant, most researchers would probably be reluctant to accept that a homogeneous effect size has been demonstrated. Certainly, visual inspection of the r values does not suggest homogeneity.

Test 28q: Procedure for obtaining a combined effect size for k studies Rosenthal (1993) employs Equation 28.90 to compute a combined/pooled effect size for k studies.

$$\bar{z}_{r_k} = \frac{\sum_{j=1}^k z_{r_j}}{k} \quad \text{(Equation 28.90)}$$

Where: z_{r_j} represents the Fisher transformed z_r value for the j^{th} study
 \bar{z}_{r_k} represents the average Fisher transformed z_r value computed for the k published studies

The following protocol is employed in using the Equation 28.90: a) Obtain the sum of the Fisher transformed z_r values for the k studies, and divide that sum by k ; and b) Employing [Table A17](#), convert the value computed for \bar{z}_{r_k} into its corresponding r value. The latter value represents the combined effect size for the k studies. Employing part a) of the aforementioned protocol, through use of Equation 28.90 the value $\bar{z}_{r_k} = .321$ is computed. Employing [Table A17](#) the latter value is converted into $r = .31$, which is the combined/pooled effect size.

$$\bar{z}_{r_k} = \frac{.693 + .549 + .203 + .310 + (-.151)}{5} = \frac{1.604}{5} = .321$$

Rosenthal (1993) notes that, if one wished to weight studies on the basis of their sample size, the value $\bar{z}_{r_k} = .351$ computed with Equation 28.25 in the previous section can be used to represent the average Fisher transformed z_r value (he also states weighting can be done on the basis of other criteria, such as the relative quality of the studies). The r value that corresponds to the Fisher transformed value $\bar{z}_{r_k} = .351$ is $r = .34$, which will represent the combined/pooled effect size. Using Cohen's (1977, 1988) criteria (for an r value), the unweighted value $r = .31$ and the weighted value $r = .34$ both fall at the lower bound of the range for a medium effect size (the effect size criteria for an r value are noted on page 838).

Rosenthal (1993) states, that one should view a combined effect size value with extreme caution when there is reason to believe that the k effect sizes employed in determining it were not homogeneous. Certainly, in such a case, the computed value for the combined effect size is little more than an average of a group of heterogeneous scores, and not reflective of a consistent effect size across studies. In view of this, in order for the combined effect size value computed with Equation 28.90 to be meaningful, it should have been previously demonstrated that the effect sizes for the k studies are relatively homogeneous. As noted earlier, the latter is questionable in our example, in spite of the fact that the result obtained with Equation 28.89 did not achieve statistical significance.

In the final analysis, one should view combined/pooled probability and effect size values computed in meta-analysis as rough estimates. These values are subject to change as more data on a hypothesis become available. Certainly, if at a given point in time the available data reflect what is true in the underlying populations, the values generated in a meta-analysis will be reasonably accurate and not change substantially after additional data become available.

Practical implications of magnitude of effect size value Before closing this section, a comment is in order concerning the relationship between the magnitude of an effect size and its practical implications regarding the relationship that exists between the independent and dependent variable. Rosnow and Rosenthal (1989) provide an interesting example (based on a study by the Steering Committee of the Physicians Health Study Research Group (1988)) involving the use of the **phi coefficient**. These authors illustrate that a low correlation coefficient (in this case the correlation is computed with the **phi coefficient**) need not necessarily indicate that the relationship between two variables is trivial. [Table 28.11](#) summarizes the results of the study, which evaluated the effect of aspirin versus a placebo on heart attacks.

In order to determine whether the result of the study is statistically significant, we evaluate the data with the **chi-square test for $r \times c$ tables**. Employing Equation 16.2, the computed chi-square value for [Table 28.11](#) is $\chi^2 = 25.01$. Since $r = 2$ and $c = 2$, the degrees of freedom are computed to be $df = (2 - 1)(2 - 1) = 1$. Employing [Table A4](#), we determine that the tabled critical .05 and .01 chi-square values for $df = 1$ are $\chi^2_{.05} = 3.84$ and $\chi^2_{.01} = 6.63$. Since the computed value $\chi^2 = 25.01$ is greater than both of the aforementioned critical values, the null

Table 28.11 Summary of Data for Heart Attack Study

		Y variable		Row sums
		Heart attack = 0	No heart attack = 1	
X variable	Aspirin = 0	104	10,933	11,037
	Placebo = 0	189	10,845	11,034
Column sums		293	21,778	22,071

hypothesis can be rejected at both the .05 and .01 levels. The actual probability value associated with the result is less than .001.

Now let us compute the magnitude of effect size for the study. Both Equations 16.18 and 28.1 (as well as Equation 28.83) can be employed to compute the **phi coefficient** (which as noted earlier in this section can be viewed as an r value within the context of meta-analysis). Employing Equation 16.18, the value $\phi = \sqrt{\chi^2/n} = \sqrt{25.01/22071} = .034$ is computed. As noted earlier, Equation 28.1 can also be employed to compute the value of **phi** (as is done with the data in Table 28.3). Thus, we designate the independent variable (which is comprised of the following two levels: aspirin versus placebo) as the X variable. The value 0 will be assigned as the X score for any subject who received aspirin, and the value 1 will be assigned as the X score for any subject who received the placebo. The dependent variable, which is whether or not a subject had a heart attack, will be the Y variable. The value 0 will be assigned as the Y score for any subject who had a heart attack, and the value 1 will be assigned as the Y score for any subject who did not have a heart attack. Employing the same protocol that is used to analyze the data in Table 28.3, we compute the following values for Table 28.11: $\Sigma X = \Sigma X^2 = 11034$; $\Sigma Y = \Sigma Y^2 = 21778$; $\Sigma XY = 10845$; $n = 22071$. When the aforementioned values are substituted in Equation 28.1, the value $r = -.034$ is computed, which is the same absolute value that is computed with Equation 16.18 for the **phi coefficient** (which can only be a positive value).

The square of $\phi = .034$ ($r = -.034$) is $\phi^2 = r^2 = .001156$. Earlier in the book it was noted that the latter value, which represents the **coefficient of determination**, is commonly employed as a measure of **effect size** for a 2×2 contingency table. The value $r^2 = .001156$ indicates that .1156% of the variability on the dependent variable can be accounted for on the basis of variability on the independent variable. Since .1156% is such a small value, one might get the impression that there is little if any relationship between taking aspirin and having a heart attack. Given the fact that the sample is comprised of 22,071 observations, it is not at all surprising that the probability value .001 is obtained when the **chi-square test for $r \times c$ tables** is employed to analyze the data. A sample size of this magnitude insures that the power of the **chi-square test** will be large enough to identify as statistically significant even a minimum effect size. Yet when Equation 16.24 is employed with the same data to compute the **odds ratio** (discussed in Section VI of the **chi-square test for $r \times c$ tables**), we obtain the value $o = 1.83$: $o = [(10933)(189)]/[(104)(10845)] = 1.83$. The value $o = 1.83$ indicates that the odds of a person who received the placebo having a heart attack are 1.83 times larger than the odds of a person who received aspirin having a heart attack. If we employ **relative risk** as a measure (also discussed in Section VI of the **chi-square test for $r \times c$ tables**), through use of Equation 16.22, we can determine that the **relative risk** of having a heart attack if one received the placebo as opposed to getting an aspirin is $[(189)/(11037)]/[(104)/(11034)] = 1.82$. The latter value indicates that someone taking the placebo is 1.82 times more likely to have a heart attack than someone taking aspirin.⁴⁶ The values computed for the **odds ratio** and **relative risk** clearly indicate that there is a definite advantage to a subject taking aspirin. In point of fact, since the researchers came to the latter conclusion, they terminated the study while it was still in progress — deeming it unethical to deprive the control subjects (i.e., the placebo group) of aspirin.⁴⁷

What can we conclude from the above example? As Cohen (1977, 1988) and Rosenthal (1991, 1993) note, there are circumstances when the strength of a relationship between an independent and dependent variable will be greater than the magnitude suggested by the coefficient of determination. A small r^2 value does not necessarily mean the relationship between the experimental variables is trivial, and is of no practical consequence. In the final analysis, depending upon how one expresses effect size, it is conceivable that a researcher may draw different conclusions regarding the strength of the relationship between the variables under study.

In closing this discussion, it should be emphasized that there are procedures and issues related to meta-analysis that have not been covered in this book. For a more comprehensive discussion of meta-analysis, the reader should consult Hedges and Olkin (1985), Mullen and Rosenthal (1985), Rosenthal (1991, 1993), and Wolfe (1986).⁴⁸ Hunt (1997) provides a good nonmathematical summary of the history and application of meta-analysis in the scientific community.

The significance test controversy As noted throughout this book, the traditional hypothesis testing model employs a null hypothesis and an alternative hypothesis. The null hypothesis is a statement of zero difference, which is commensurate with saying that in the underlying population(s) there is zero effect/correlation present. During the past 25 years an increasing number of researchers and statisticians have become critical of the conventional hypothesis testing model. Among those who have addressed this issue are Cohen (1994), Harlow *et al.* (1997), Meehl (1978), Morrison and Henkel (1970), Murphy and Myers (1998), and Serlin and Lapsley (1985, 1993).

The crux of the argument against the traditional hypothesis testing model is that, in reality, the null hypothesis is always false. Specifically, various sources note that the null hypothesis is a **point hypothesis**, in that it stipulates a precise value — namely zero — for the difference between the experimental conditions. Thus, any difference, no matter how negligible, will provide sufficient grounds for rejecting the null hypothesis. It has been pointed out by numerous researchers that the actual difference between two experimental conditions is probably never exactly equal to zero. Although admittedly a difference may be close to zero, if our measuring instrument is sufficiently sensitive and we carry our measurements out to many decimal places, we will probably never record a difference that is exactly equal to zero. And if the latter is true, it means that the null hypothesis will always be false.

If, in fact, the null hypothesis is always false, it logically follows that it is not possible to commit a Type I error (which is rejecting a true null hypothesis). If a Type I error becomes impossible, then the only type of error a researcher need concern herself with is a Type II error (which is not rejecting a false null hypothesis). It was noted earlier in the book, that the likelihood of committing a Type II error is inversely related to the power of a statistical test — i.e., the more powerful the test, the lower the likelihood of committing a Type II error. If a researcher wishes to achieve a specific level of power for a statistical test, prior to conducting the test one must stipulate the magnitude of effect size one is trying to detect. The smaller the effect size, the greater the power that will be required for the test. There are essentially three ways a researcher can increase the power of a statistical test. They are: a) Reduction of error variability; b) Increasing the value of alpha (i.e., p value) employed in determining statistical significance; and c) Increasing the size of the sample. If a researcher assumes she is unable to reduce error variability any more than she already has, in order to increase power she must either employ a higher p value and/or increase the size of the sample employed in a study. Since current scientific convention does not endorse the use of an alpha level larger than .05, at this point in time it probably isn't reasonable to expect that higher alpha levels will be an acceptable mechanism for increasing power. Thus, the most practical and effective way to maximize power is by increasing

sample size. How large a sample one employs should be dictated by the magnitude of effect size one is trying to detect (which obviously involves a subjective decision on the part of a researcher). Within the context of the traditional hypothesis testing model, it will require a relatively large sample size to declare a result significant if the effect size present is small or even in the low medium range. As Murphy and Myers (1998) note, the outcome of a test of statistical significance employed within the traditional model provides more of a commentary on the power of the statistical test than it does on the strength of the relationship (i.e., effect size) between the variables under study.

In the final analysis, since the null hypothesis is always wrong, Murphy and Myers (1998) state that a researcher can never design a study that has too much power. They recommend that in reference to the effect size one is trying to detect, whenever possible the power of a test should be at least .50, and ideally .80 or greater. If the power of a study is so low that there is little likelihood of detecting the hypothesized effect size, the study probably isn't worth conducting. Consequently, prior to conducting a study a researcher should determine (based on previous research or theoretical conjecture) what she considers to be a meaningful effect size, and employ a large enough sample to insure a reasonable likelihood of detecting it (if, in fact, it is present).

The minimum-effect hypothesis testing model An alternative that has been suggested to the traditional hypothesis testing model is the **minimum-effect hypothesis testing model**, which is described in detail by Murphy and Moyers (1998). Based on papers by, among others, Meehl (1978) and Serlin and Lapsley (1985, 1993), the model employs the null hypothesis to stipulate a value below which any effect present in the data would be viewed as trivial, and above which would be meaningful. As an example, if one were comparing the IQ scores of two groups, the null hypothesis might stipulate a difference between 0 and 5 points, while the alternative hypothesis would stipulate a difference greater than five points. In such a case, any difference of five points or less would result in retaining the null hypothesis, since a difference within that range would be considered trivial (i.e., of no practical or theoretical value). A difference of more than five points would lead to rejection of the null hypothesis, since a difference equal to or greater than five points would be considered meaningful. Note that the null hypothesis in the minimum-effect model stipulates a range of values, whereas in the traditional hypothesis testing model the null hypothesis stipulates a point (i.e., a specific value).

Murphy and Moyers (1998) discuss stipulating differences within the minimum-effect hypothesis testing model in terms of effect size. They suggest the null hypothesis could stipulate a range of values in which the effects of the treatment account for what is considered to be a negligible/trivial amount of variability. They suggest one might stipulate in the null hypothesis that between 0 and 1% of variance on the dependent variable can be accounted for by variation on the independent variable. The alternative hypothesis would be supported if an effect size of greater than 1% is detected. The value of 1% corresponds to the lower limit of Cohen's (1977, 1988) minimum value for a small effect size noted earlier in this section, when an r value is employed to measure effect size (i.e., $r^2 = (.1)^2 = .01$, which, expressed as a percentage, is 1%). Murphy and Moyers (1998) have developed special tables based on the **noncentral F distribution** (alluded to previously in Section VI of the **single-factor between-subjects analysis of variance** under the discussion of **power**) for evaluating a minimum-effect null hypothesis. In contrast to the **central F distribution**, which has been used throughout the book for evaluating F values within the context of the traditional hypothesis testing model, the noncentral F distribution can be employed to evaluate a minimum-effect null hypothesis. The tables developed by Murphy and Moyers (1998) allow for testing significance at the .05 and .01 levels, and also provide for an analysis of power. In addition to evaluating a minimum-effect null hypothesis that stipulates an effect size of 1% or less as a trivial, the tables also evaluate a null hypothesis that stipulates an effect size of 5% or less as a trivial (since Murphy and Moyers (1998) believe some

researchers might prefer to employ the latter value as the upper limit for a trivial effect). Murphy and Moyers (1998) also provide equations for converting various test statistics (e.g., χ^2 , R^2 , etc.) into F values, in order that they can be employed with the tables for the noncentral F distribution. It should be noted that for a given set of data, the minimum-effect hypothesis testing model will have lower power than the traditional hypothesis testing model. This is the case, since it is easier to reject a null hypothesis stipulating a zero difference than it is to reject a null hypothesis that stipulates a range of values between zero and some number above it. Murphy and Moyers (1998) note that the loss of power is offset by the fact that the minimum-effect model provides the researcher with more meaningful results.

The minimum-effect hypothesis testing model is more compatible with the hypothesis testing philosophies of the major proponents of meta-analysis (e.g., Rosenthal and Hedges) than is the traditional hypothesis testing model. In both the minimum-effect model and meta-analysis, greater emphasis is placed on effect size than on the level of significance. In the final analysis, when all is said and done, regardless of which hypothesis testing model one employs, the key to effective hypothesis testing ultimately boils down to employing a representative sample that is large enough to detect any meaningful effect(s) present in the underlying population(s). Research that abides by the latter principle will ultimately yield results that are both reliable and meaningful.

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Endnotes

1. It is also possible to designate the Y variable as the predictor variable and the X variable as the criterion variable. The use of the Y variable as the predictor variable is discussed in Section VI.
2. It should be noted that when the joint distribution of two variables is bivariate normal, only a linear relationship can exist between the variables. As a result of the latter, whenever the population correlation between two bivariate normally distributed variables equals zero, one can conclude that the variables are statistically independent of one another. Under such conditions the null hypothesis $H_0: \rho = 0$ stated in this section is equivalent to the null hypothesis that the two variables are independent of one another. On the other hand, it is possible for each of two variables to be normally distributed, yet the joint distribution of the two variables not be bivariate normal. When the latter is true, it possible to compute the value $r = 0$, and at the same time have two variables that are statistically dependent upon one another. Statistical dependence in such a case will be the result of the fact that the variables are curvilinearly related to one another.
3. Howell (1992, 1997) notes that the value of r computed with Equation 28.1 is a biased estimate of the underlying population parameter ρ . The degree to which the computed value of r is biased is inversely related to the size of the sample employed in computing the correlation coefficient. For this reason, when one employs correlational data within the framework of research, it is always recommended that a reasonably large sample size be employed.

One way of correcting for bias resulting from a small sample size is to employ the equation noted below to compute the value \tilde{r} , which represents a relatively unbiased estimate of the population parameter ρ . The value \tilde{r} is referred to as a “shrunk” or “adjusted” estimate of the population correlation. The computation of \tilde{r} (the absolute value of which will always be less than r) is demonstrated for Example 28.1.

$$\tilde{r} = \sqrt{1 - \frac{(1 - r^2)(n - 1)}{n - 2}} = \sqrt{1 - \frac{[1 - (.955)^2][5 - 1]}{5 - 2}} = .940$$

Thus, in the case of Example 28.1, $\tilde{r} = .940$ provides a better estimate of the true population correlation than $r = .955$ (although even if \tilde{r} is employed, $n = 5$ is an absurdly low sample size to employ within the framework of serious research). Since most sources use the computed value of r rather than \tilde{r} , the former value will be employed as the estimate of the population correlation throughout the discussion of the **Pearson product-moment correlation coefficient**.

4. An alternative form of Equation 28.3 that is based on the relationship $t^2 = F$ (described in Section VII of the **single-factor between-subjects analysis of variance**), which yields equivalent results, employs the F distribution. The equation employing the F distribution for evaluating the significance of r is noted below.

$$F = \frac{r^2(n - 2)}{1 - r^2}$$

Employing the above equation with Example 28.1, the value $F = 31.10$ is computed.

$$F = \frac{(.955)^2(5 - 3)}{1 - (.955)^2} = 31.10$$

The computed value $F = 31.10$ (which is equivalent to $(t = 5.58)^2$ if rounding off error is ignored) is evaluated with **Table A10**. The degrees of freedom employed in evaluating the above equation are $df_{\text{num}} = 1$, $df_{\text{den}} = n - 2$. Thus, $df_{\text{num}} = 1$ and $df_{\text{den}} = 3$. It is determined that the tabled critical .05 and .01 two-tailed values are $F_{.05} = 10.13$ and $F_{.01} = 34.12$, and the tabled critical .05 and .01 one-tailed values are $F_{.05} = 5.54$ and $F_{.01} = 20.61$. (The latter values, which are not in **Table A10**, were obtained by squaring the tabled critical one-tailed values $t_{.05} = 2.35$ and $t_{.01} = 4.54$. A full discussion of one-tailed F values can be found in Section VI of the **t test for two independent samples** under the discussion of homogeneity of variance.) The same guidelines for interpreting a computed t value with Equation 28.3 are employed to interpret the computed F value, with one exception in reference to the directional alternative hypothesis $H_1: \rho < 0$. Since the value of F will always be a positive number, if the directional alternative $H_1: \rho < 0$ is employed, in order to reject the null hypothesis the value of F must be equal to or greater than the tabled critical one-tailed F value at the prespecified level of significance. However, the sign of r must be negative. When the F distribution is employed to evaluate the null hypothesis $H_0: \rho = 0$, it results in identical conclusions to those reached when Equation 28.3 is employed. Specifically, the nondirectional alternative hypothesis $H_1: \rho \neq 0$ is supported at the .05 level, since $F = 31.10$ is greater than the tabled critical two-tailed value $F_{.05} = 10.13$. The directional alternative hypothesis $H_1: \rho > 0$ is supported at both the .05 and .01 levels, since r is a positive number, and $F = 31.10$ is greater than the tabled critical one-tailed values $F_{.05} = 5.54$ and $F_{.01} = 20.61$.

Marascuilo and Serlin (1988) note that the following equation employing the normal distribution can also be used with large sample sizes to evaluate the null hypothesis $H_0: \rho = 0$: $z = r\sqrt{n - 1}$. If applied to Example 28.1, the value $z = (.955)\sqrt{5 - 1} = 1.91$ is computed. The value $z = 1.91$ only supports the directional alternative hypothesis

$H_1: \rho > 0$ at the .05 level, since $z = 1.91$ is greater than the tabled critical one-tailed value $z_{.05} = 1.65$ in **Table A1** in the **Appendix**. The nondirectional alternative hypothesis $H_1: \rho \neq 0$ is not supported, since $z = 1.91$ is less than the tabled critical two-tailed value $z_{.05} = 1.96$. The latter result indicates that when employed with a small sample size, the normal approximation provides a more conservative test of an alternative hypothesis than does Equation 28.3.

5. a) The value $(1 - r^2)$ is often referred to as the **coefficient of nondetermination**, since it represents the proportion of variance that the two variables do not hold in common with one another. Further discussion of the **coefficient of determination** can be found in Section IX (the **Addendum**) in the discussion of **meta-analysis and related topics**; b) Ozer (1985) argues that under certain conditions it is more prudent to employ $|r|$ as a measure of the proportion of variance on one variable that can be accounted for by variability on the other variable. Cohen (1988, p. 533) succinctly summarizes Ozer's (1985) point by noting that when there is reason to believe that a causal relationship exists between X and Y , the value r^2 provides an appropriate estimate of the percentage/proportion of variance on Y attributable to X . However, if there is reason to believe that both X and Y are caused by a third variable, the absolute value of r is a more appropriate measure to employ to represent the proportion of shared variance between X and Y .
6. The reader should keep in mind that for illustrative purposes the sample size employed for Example 28.1 is very small. Consequently, the values r and r^2 are, in all likelihood, not accurate estimates of the corresponding underlying population parameters ρ and ρ^2 .
7. An equation that is based on the minimum squared distance of all the points from the line reflects the fact that if the distance of each data point from the line is measured, and the resulting value is squared, the sum of the squared values for the n data points is the lowest possible value that can be obtained for that set of data.
8. The values $s_{Y.X}$ and $s_{X.Y}$ can also be computed with the equations noted below:

$$s_{Y.X} = \sqrt{\frac{SS_Y - \frac{(SP_{XY})^2}{SS_X}}{n - 2}} = \sqrt{\frac{29.2 - \frac{(88.6)^2}{294.8}}{5 - 2}} = .92$$

$$s_{X.Y} = \sqrt{\frac{SS_X - \frac{(SP_{XY})^2}{SS_Y}}{n - 2}} = \sqrt{\frac{294.8 - \frac{(88.6)^2}{29.2}}{5 - 2}} = 2.94$$

9. The reader may find it useful to review the discussion of confidence intervals in Section VI of the **single-sample t test** before reading this section.
10. The term SS_X in Equation 28.14 may also be written in the form $SS_X = (n - 1)\bar{s}_X^2$, and the term SS_Y in Equation 28.15 may also be written in the form $SS_Y = (n - 1)\bar{s}_Y^2$.

11. Zar (1999, p. 382) notes that the following equation can be employed to convert a z_r value into an r value: $r = (e^{2z_r} - 1)/(e^{2z_r} + 1)$. Thus, if

$$z_r = 1.886, r = [(2.71828)^{(2)(1.886)} - 1]/[(2.71828)^{(2)(1.886)} + 1] = .955.$$

The equation $r = \tanh z_r$ can also be employed to convert a z_r value into an r value (where \tanh represents the **hyperbolic tangent** of a number). Thus, $\tanh 1.886 = .955$. Scientific calculators generally have keys that allow for quick computation of a \tanh value.

12. Equation 28.20 can also be written in the form: $z = (z_r - z_{p0})\sqrt{n - 3}$. Thus, $z = (1.886 - 1.099)\sqrt{5 - 3} = 1.11$.
13. The value $n = 5$ employed in Example 28.1 is not used, since the method to be described is recommended when $n \geq 25$. For smaller sample sizes, tables in Cohen (1977, 1988) derived by David (1938) can be employed.
14. For the analysis described in this section the $df = \infty$ curve is employed for the relevant set of power curves, since **Fisher's z_r transformation** is based on the normal distribution.
15. Equation 28.24 can also be employed to evaluate the hypothesis of whether there is a significant difference between $k = 2$ independent correlations — i.e., the same hypothesis evaluated with Equation 28.22. When $k = 2$, the result obtained with Equation 28.24 will be equivalent to the result obtained with Equation 28.22. Specifically, the square of the obtained value of z obtained with Equation 28.22 will equal the value of χ^2 obtained with Equation 28.24. Thus, if the data employed in Equation 28.22 are employed in Equation 28.24, the obtained value of chi-square equals $\chi^2 = z^2 = (.878)^2 = .771$.

$$\chi^2 = [(5 - 3)(1.886)^2 + (5 - 3)(1.008)^2] - \frac{[(5 - 3)(1.886) + (5 - 3)(1.008)]^2}{(5 - 3) + (5 - 3)} = .771$$

16. When $k = 2$, Equation 28.25 is equivalent to Equation 28.23.
17. If homogeneity of variance is assumed for the two samples, a pooled error variance can be computed as follows:

$$s_{Y.X}^2 = \frac{(n_1 - 2)(s_{Y.X_1}^2) + (n_2 - 2)(s_{Y.X_2}^2)}{n_1 + n_2 - 4}$$

$$s_{X.Y}^2 = \frac{(n_1 - 2)(s_{X.Y_1}^2) + (n_2 - 2)(s_{X.Y_2}^2)}{n_1 + n_2 - 4}$$

The computed value $s_{Y.X}^2$ is used in place of both $s_{Y.X_1}^2$ and $s_{Y.X_2}^2$ in Equation 28.31, and the computed value $s_{X.Y}^2$ is used in place of both $s_{X.Y_1}^2$ and $s_{X.Y_2}^2$ in Equation 28.32.

18. Marascuilo and Serlin (1988) describe how the procedure described in this section can be extended to the evaluation of a hypothesis contrasting three or more regression coefficients.

19. The equations for z_{X_i} and z_{Y_i} are analogous to Equation I.27 in the **Introduction** (which employs the population parameters μ and σ in computing a z score).
20. The sum of products within this context is not the same as the sum of products that represents the numerator of Equation 28.1.
21. One way of avoiding the problem of dependent pairs is to form pairs in which no digit is used for more than one pair. In other words, the first two digits in the series represent the X and Y variables for first pair, the third and fourth digits in the series represent the X and Y variables for second pair, and so on. Although use of the latter methodology really does not conform to the definition of autocorrelation, if it is employed one can justify employing the critical values in **Table A16**.
22. A discussion of the derivation of Equation 28.41 can be found in Bennett and Franklin (1954).
23. The reader should take note of the fact that the data for Example 28.5 are fictitious and, in reality the result of the analysis in this section may not be consistent with actual studies that have been conducted which evaluate the relationship between intelligence and eye-hand coordination.
24. Although the **phi coefficient** is described in the book as a measure of association for the **chi-square test for $r \times c$ tables** (specifically, for 2×2 tables), it is also employed in psychological testing as a measure of association for 2×2 tables in order to evaluate the consistency of n subjects' responses to two questions. The latter type of analysis is essentially a dependent samples analysis for a 2×2 table, which, in fact, is the general model for which the **McNemar test (Test 20)** is employed.
25. It is also the case that the greater the number of predictor variables in a set of data involving a fixed number of subjects, the larger the value of R^2 .
26. This principle has obviously not been adhered to in the example under discussion in order to minimize computations.
27. Tabachnick and Fidell (1989, 1996) note that, for small sample sizes, some sources recommend an even more severe adjustment than that which results from using Equation 28.56.
28. The equation noted below is equivalent to Equation 28.62.

$$s_{Y \cdot X_1 X_2} = \sqrt{\frac{SS_Y(1 - R_{Y \cdot X_1 X_2}^2)}{n - k - 1}} = \sqrt{\frac{(29.2)(1 - .944)}{5 - 2 - 1}} = .90$$

29. The following should be noted with respect to Equation 28.69: a) When the sample size is small and/or the number of subjects is not substantially larger than the number of predictor variables, the "shrunk" estimate \tilde{R}^2 (computed with Equation 28.56) should be employed in Equation 28.69; b) When there are more than two predictor variables, the multiple correlation coefficient for the k variables is employed in the numerator of the radical of

Equation 28.69 in place of $R_{Y \cdot X_1 X_2}^2$. The value $r_{X_1 X_2}^2$ in the denominator of the radical of Equation 28.69 is replaced by the squared multiple correlation coefficient of variable i with all of the remaining predictor variables. Thus, if there are three predictor variables and s_{b_1} is computed, the values employed in the numerator and denominator of the radical are, respectively, $R_{Y \cdot X_1 X_2 X_3}^2$ and $R_{X_1 \cdot X_2 X_3}^2$.

30. Howell (1992, 1997) cites sources who argue that the t distribution does not provide a precise approximation of the underlying sampling distribution for the standard error of estimate of the coefficients. On the basis of this he states that caution should be employed in interpreting the results of the t test.
31. The same results are obtained if the analysis is done employing the standardized regression coefficients. This is demonstrated below employing the appropriate equations for the standardized coefficients. The minimal discrepancy between the values t_{β_1} and t_{b_1} is due to rounding off error.

$$s_{\beta_i} = \sqrt{\frac{1 - R_{Y \cdot X_1 X_2}^2}{(1 - r_{X_1 X_2}^2)(n - k - 1)}} = \sqrt{\frac{1 - .944}{[1 - (.37)^2][5 - 2 - 1]}} = .180$$

$$t_{\beta_i} = \frac{\beta_i}{s_{\beta_i}} \quad t_{\beta_1} = \frac{.883}{.180} = 4.91 \quad t_{\beta_2} = \frac{.193}{.180} = 1.07$$

32. Marascuilo and Levin (1983) and Marascuilo and Serlin (1988) recommend that in order to control the Type I error rate, a more conservative t value should be employed when the number of regression coefficients evaluated is greater than one. These sources describe the use of the **Bonferroni–Dunn** and **Scheffé procedures** (which are described in reference to multiple comparisons for analysis of variance procedures) in adjusting the t value.
33. The computed value r_p can also be evaluated through use of the critical values in **Table A16** (for $df = n - v$).
34. Note that when a simple bivariate/zero order correlation is computed, $n - v = n - 2$, and thus Equation 28.73 becomes identical to Equation 28.3 (which is used to evaluate the significance of the zero order correlation coefficient $r_{X_1 X_2}$).
35. The computed value r_{sp} can also be evaluated through use of the critical values in **Table A16** (for $df = n - v$).
36. As is the case for Equation 28.73, Equation 28.75 becomes identical to Equation 28.3 when $n - v = n - 2$.
37. Cohen (1977, 1988) also discusses additional effect size indices that are employed for computing the power of various multivariate procedures.
38. a) The values that Cohen (1977; 1988, pp. 24–27) employs for identifying a small versus medium versus large effect size for the ***d* index** and other indices to be described in this

section were developed in reference to behavioral science research. Although these values can be employed for research in areas other than the behavioral sciences, it is conceivable that practitioners in other disciplines may elect to employ different values which they deem more appropriate for their area of specialization; b) Equation 28.77 can also be employed to convert an **omega squared** value ($\hat{\omega}^2$) (discussed in Section VI of the **t test for two independent samples**) into a d value. If the values .0099, .0588, and .1379 (which are Cohen's lower limits for **omega squared** for a small, medium, and large effect size) are employed to represent r^2 in Equation 28.77, they yield the following corresponding d values: .2, .5, and .8; c) Further clarification of the relationship between r and Cohen's **d index** can be found in Cohen (1977; 1988, pp. 81–83).

39. Although **Cohen's d index** is also used as a measure of effect size within the framework of meta-analysis, Rosenthal (1991, pp. 17–18) argues that the use of an r value is preferable to the use of a d value as a measure of effect size.
40. The author is indebted to Robert Rosenthal for clarifying some of the issues discussed in this section.
41. It is important to emphasize that researchers are often not in agreement with regard to the most appropriate estimate of effect size to employ. Hopefully, if an effect of some magnitude is present which has theoretical or practical implications, regardless of which measure of effect size one employs, a reasonably accurate estimate of the effect size will emerge from an analysis.
42. a) The same test result will be obtained if the z value for *Study E* is assigned a positive sign, and the z values for *Studies A, B, C, and D* are assigned negative signs; b) If in a given study the means of the two groups are equal, the p value for that study will equal .50, and the corresponding z value will equal 0.
43. Rosenthal (1991) presents a modified form of Equation 28.86 that allows a researcher to differentially weight the k studies employed in a meta-analysis. A weighting system is employed within this context to reflect the relative quality of each of the studies. The magnitude of the weights (which are assigned by a panel of judges) are supposed to be a direct function of the quality of a study.
44. It is interesting to note that the average z value for five studies is $\bar{z}_k = .95$, and that the latter z value in itself is not statistically significant. It is quite common for Equation 28.86 to yield a significant combined p value when the average z value in itself is not statistically significant.
45. The same test result will be obtained if, instead, we assign a negative sign to the Fisher transformed z_r values for *Studies A, B, C, and D*, and a positive sign for the Fisher transformed z_r value for *Study E*.
46. As noted under the discussion of the **odds ratio** in Section VI of the **chi-square test for $r \times c$ tables**, the values of the **odds ratio** and the **relative risk** will be very close together when the event in question (in this case a heart attack) has a low probability of occurring. The likelihood of someone in the placebo group having a heart attack is $189/11034 = .01713$, while the likelihood of someone in the aspirin group having a heart attack is

$104/11037 = .00942$ (note that $.01713/.00942 = 1.82$, which is the value of **relative risk**). Thus, the values computed for the **odds ratio** and the **relative risk** are almost identical.

47. An alternative way of presenting effect size for a contingency table which (like the **odds ratio**) may make it more apparent if a seemingly small effect is of practical consequence is the **binomial effect size display (BESD)** developed by Rosenthal and Rubin (1982).
48. Wolf (1986) describes a nonparametric measure of effect size that can be employed in meta-analysis.

Test 29

Spearman's Rank-Order Correlation Coefficient (Nonparametric Measure of Association/Correlation Employed with Ordinal Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Spearman's rank-order correlation coefficient is one of a number of measures of correlation or association discussed in this book. Measures of correlation are not inferential statistical tests, but are, instead, descriptive statistical measures that represent the degree of relationship between two or more variables. Upon computing a measure of correlation, it is common practice to employ one or more inferential statistical tests in order to evaluate one or more hypotheses concerning the correlation coefficient. The hypothesis stated below is the most commonly evaluated hypothesis for **Spearman's rank-order correlation coefficient**.

Hypothesis evaluated with test In the underlying population represented by a sample, is the correlation between subjects' scores on two variables some value other than zero? The latter hypothesis can also be stated in the following form: In the underlying population represented by the sample, is there a significant **monotonic** relationship between the two variables? It is important to note that the nature of the relationship described by **Spearman's rank-order correlation coefficient** is based on an analysis of two sets of ranks.

Relevant background information on test Prior to reading the material in this section the reader should review the general discussion of correlation in Section I of the **Pearson product-moment correlation coefficient (Test 28)**. Developed by Spearman (1904), **Spearman's rank-order correlation coefficient** is a bivariate measure of correlation/association that is employed with rank-order data. The population parameter estimated by the correlation coefficient will be represented by the notation ρ_s (where ρ is the lower case Greek letter **rho**). The sample statistic computed to estimate the value of ρ_s will be represented by the notation r_s . In point of fact, **Spearman's rank-order correlation coefficient** is a special case of the **Pearson product-moment correlation coefficient**, when the latter measure is computed for two sets of ranks. The relationship between **Spearman's rank-order correlation coefficient** and the **Pearson product-moment correlation coefficient** is discussed in Section VI.

As is the case for the **Pearson product-moment correlation coefficient**, **Spearman's rank-order correlation coefficient** can be employed to evaluate data for n subjects, each of whom has contributed a score on two variables (designated as the X and Y variables). Within each of the variables, the n scores are rank-ordered. **Spearman's rank-order correlation coefficient** is also commonly employed to evaluate the degree of agreement between the rankings of $m = 2$ judges for n subjects/objects.

In computing **Spearman's rank-order correlation coefficient**, one of the following is true with regard to the rank-order data that are evaluated: a) The data for both variables are in a rank-order format, since it is the only format for which data are available; b) The original data are in

a rank-order format for one variable and in an interval/ratio format for the second variable. In such an instance, data on the second variable are converted to a rank-order format in order that both sets of data represent the same level of measurement; and c) The data for both variables have been transformed into a rank order-format from an interval/ratio format, since the researcher has reason to believe that one or more of the assumptions underlying the **Pearson product-moment correlation coefficient** (which is the analogous parametric correlational procedure employed for interval/ratio data) have been saliently violated. It should be noted that since information is sacrificed when interval/ratio data are transformed into a rank-order format, some researchers may elect to employ the **Pearson product-moment correlation coefficient** rather than **Spearman's rank-order correlation coefficient**, even when there is reason to believe that one or more of the assumptions of the former measure have been violated.

Spearman's rank-order correlation coefficient determines the degree to which a **monotonic** relationship exists between two variables. A monotonic relationship can be described as **monotonic increasing** (which is associated with a positive correlation) or **monotonic decreasing** (which is associated with a negative correlation). A relationship between two variables is monotonic increasing, if an increase in the value of one variable is always accompanied by an increase in the value of the other variable. A relationship between two variables is monotonic decreasing, if an increase in the value of one variable is always accompanied by a decrease in the value of the other variable. Based on the above definitions, a positively sloped straight line represents an example of a monotonic increasing function, while a negatively sloped straight line represents an example of a monotonic decreasing function. In addition to the aforementioned linear functions, curvilinear functions can also be monotonic. For instance, the function $Y = X^2$ depicted in Figure 29.1 represents an example of a monotonic increasing function, since an increase in the X variable always results in an increase in Y variable. It should be noted that when the interval/ratio scores on two variables are monotonically related to one another, a linear function can be employed to describe the relationship between the rank-orderings of the two variables. This latter fact is demonstrated in Section VI.

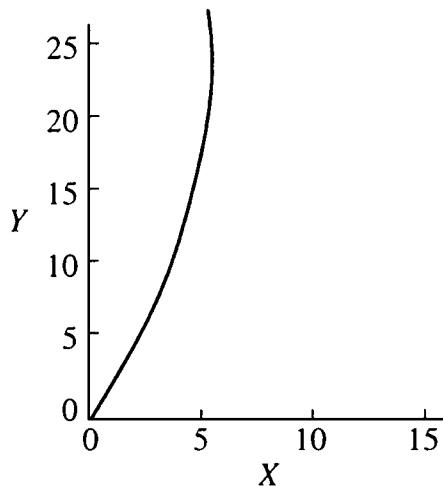


Figure 29.1 Monotonic Increasing Relationship ($Y = X^2$)

The same general guidelines that are described for interpreting the value of the **Pearson product-moment correlation coefficient** can be applied to **Spearman's rank-order correlation coefficient**. Thus, the range of values r_s can assume is defined by the limits -1 to $+1$ (i.e., $-1 \leq r_s \leq +1$). The absolute value of r_s (i.e., $|r_s|$) indicates the strength of the relationship

between the two variables. As the absolute value of r_s approaches 1, the strength of the monotonic relationship increases, being the strongest when r_s equals either +1 or -1. The closer the absolute value of r_s is to 0, the weaker the monotonic relationship between the two variables, and, when $r_s = 0$, no monotonic relationship is present. The sign of r_s indicates the direction of the monotonic relationship (i.e., positive/increasing monotonic versus negative/decreasing monotonic). As is the case for the **Pearson product-moment correlation coefficient**, a positive correlation indicates that an increase (decrease) on one variable is associated with an increase (decrease) on the other variable. A negative correlation indicates that an increase (decrease) on one variable is associated with a decrease (increase) on the other variable.

It is important to note that correlation does not imply causation. Consequently, if there is a strong correlation between two variables (i.e., the absolute value of r_s is close to 1), a researcher is not justified in concluding that one variable causes the other variable. Although it is possible that when a strong correlation exists one variable may, in fact, cause the other variable, the information employed in computing **Spearman's rank-order correlation coefficient** does not allow a researcher to draw such a conclusion. This is the case, since extraneous variables that have not been taken into account by the researcher can be responsible for the observed correlation between the two variables.

II. Example

Example 29.1 is identical to Example 28.1 (which is evaluated with the **Pearson product-moment correlation coefficient**). In evaluating Example 29.1 it will be assumed that the ratio data are rank-ordered, since one or more of the assumptions of the **Pearson product-moment correlation coefficient** have been saliently violated.¹

Example 29.1 *A psychologist conducts a study employing a sample of five children to determine whether there is a statistical relationship between the number of ounces of sugar a ten-year-old child eats per week (which will represent the X variable) and the number of cavities in a child's mouth (which will represent the Y variable). The two scores (ounces of sugar consumed per week and number of cavities) obtained for each of the five children follow: **Child 1** (20, 7); **Child 2** (0, 0); **Child 3** (1, 2); **Child 4** (12, 5); **Child 5** (3, 3). Is there a significant correlation between sugar consumption and the number of cavities?*

III. Null versus Alternative Hypotheses

Upon computing **Spearman's rank-order correlation coefficient**, it is common practice to determine whether the obtained absolute value of the correlation coefficient is large enough to allow a researcher to conclude that the underlying population correlation coefficient between the two variables is some value other than zero. Section V describes how the latter hypothesis, which is stated below, can be evaluated through use of tables of critical r_s values or through use of an inferential statistical test that is based on either the t or z distributions.

Null hypothesis $H_0: \rho_s = 0$

(In the underlying population the sample represents, the correlation between the ranks of subjects on Variable X and Variable Y equals 0.)

Alternative hypothesis $H_1: \rho_s \neq 0$

(In the underlying population the sample represents, the correlation between the ranks of subjects

on Variable X and Variable Y equals some value other than 0. This is a **nondirectional alternative hypothesis**, and it is evaluated with a **two-tailed test**. Either a significant positive r_s value or a significant negative r_s value will provide support for this alternative hypothesis. In order to be significant, the obtained absolute value of r_s must be equal to or greater than the tabled critical two-tailed r_s value at the prespecified level of significance.)

or

$$H_1: \rho_s > 0$$

(In the underlying population the sample represents, the correlation between the ranks of subjects on Variable X and Variable Y equals some value greater than 0. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. Only a significant positive r_s value will provide support for this alternative hypothesis. In order to be significant (in addition to the requirement of a positive r_s value), the obtained absolute value of r_s must be equal to or greater than the tabled critical one-tailed r_s value at the prespecified level of significance.)

or

$$H_1: \rho_s < 0$$

(In the underlying population the sample represents, the correlation between the ranks of subjects on Variable X and Variable Y equals some value less than 0. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. Only a significant negative r_s value will provide support for this alternative hypothesis. In order to be significant (in addition to the requirement of a negative r_s value), the obtained absolute value of r_s must be equal to or greater than the tabled critical one-tailed r_s value at the prespecified level of significance.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis is rejected.²

IV. Test Computations

Table 29.1 summarizes the data for Example 29.1. The following should be noted with respect to Table 29.1: a) The number of subjects is $n = 5$. Each subject has an X score and a Y score, and thus there are five X scores and five Y scores; b) The rankings of the five subjects' scores on the X and Y variables are respectively recorded in the columns labelled R_X and R_Y ; c) The column labelled $d = R_X - R_Y$ contains a difference score for each subject, which is obtained by subtracting a subject's rank on the Y variable from the subject's rank on the X variable; and d) The column labelled d^2 contains the square of each subject's difference score.

Table 29.1 Summary of Data for Example 29.1

Subject	X	R_X	Y	R_Y	$d = R_X - R_Y$	d^2
1	20	5	7	5	0	0
2	0	1	0	1	0	0
3	1	2	2	2	0	0
4	12	4	5	4	0	0
5	3	3	3	3	0	0
					$\Sigma d = 0$	$\Sigma d^2 = 0$

The ranking protocol employed in [Table 29.1](#) is identical to that employed for the **Mann–Whitney U test (Test 12)**. Whereas in the case of the latter test the scores of subjects are ranked within each group, in the computation of **Spearman’s rho** the scores of the $n = 5$ subjects are ranked within each of the variables. Thus, in [Table 29.1](#) the five subjects’ X scores are ranked such that a rank of 1 is assigned to the lowest score on the X variable, a rank of 2 is assigned to the next lowest score on the X variable, and so on until a rank of 5 is assigned to the highest score on the X variable. The identical ranking procedure is employed with respect to the Y scores (i.e., a rank of 1 is assigned to the lowest score on the Y variable, a rank of 2 is assigned to the next lowest score on the Y variable, and so on until a rank of 5 is assigned to the highest score on the Y variable). In the event of tied scores (which do not occur in Example 29.1), as is the case for other rank-order procedures, the average of the ranks involved is assigned to all scores tied for a given rank.

It should be noted that it is permissible to reverse the ranking protocol described above. Specifically, for each variable a rank of 1 can be assigned to the highest score on that variable and a rank of 5 to the lowest score on that variable. Employing this alternative ranking protocol will yield the identical value for r_s as the one yielded by the ranking protocol employed in [Table 29.1](#). It should be emphasized that regardless of which ranking protocol is employed, the same protocol must be employed for both variables. The protocol of assigning the lowest rank to the lowest score and the highest rank to the highest score is employed in Example 29.1, since it allows for easiest interpretation of the results of the study.

In Column 6 of [Table 29.1](#), the sum of the difference scores is computed to be $\sum d = 0$. In point fact, $\sum d$ will always equal zero and if $\sum d$ is some value other than zero, it indicates that an error has been made in the rankings and/or computations. In the last column of [Table 29.1](#), the sum of the squared difference scores ($\sum d^2 = 0$) is computed. This latter value (which will only equal zero when $r_s = 1$) and the value of n are employed in Equation 29.1, which is the equation for computing **Spearman’s rank-order correlation coefficient**.³

$$r_s = 1 - \frac{6\sum d^2}{n(n^2 - 1)} \quad \text{(Equation 29.1)}$$

Substituting the appropriate values in Equation 29.1, the value $r_s = 1$ is computed.

$$r_s = 1 - \frac{(6)(0)}{5[(5)^2 - 1]} = 1$$

V. Interpretation of the Test Results

The obtained value $r_s = 1$ is evaluated with [Table A18 \(Table of Critical Values for Spearman’s Rho\)](#) in the **Appendix**. The critical values in [Table A18](#) are listed in reference to n .⁴ Employing [Table A18](#), it can be determined that the tabled critical two-tailed r_s value at the .05 level of significance is $r_{s_{.05}} = 1$. Because of the small sample size, it is not possible to evaluate the nondirectional null hypothesis at the .01 level. The tabled critical one-tailed r_s values at the .05 and .01 levels of significance are $r_{s_{.05}} = .90$ and $r_{s_{.01}} = 1$.

The following guidelines are employed in evaluating the null hypothesis $H_0: \rho_s = 0$.

a) If the nondirectional alternative hypothesis $H_1: \rho_s \neq 0$ is employed, the null hypothesis can be rejected if the obtained absolute value of r_s is equal to or greater than the tabled critical two-tailed value at the prespecified level of significance.

b) If the directional alternative hypothesis $H_1: \rho_s > 0$ is employed, the null hypothesis can

be rejected if the sign of r_s is positive, and the value of r_s is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

c) If the directional alternative hypothesis $H_1: \rho_s < 0$ is employed, the null hypothesis can be rejected if the sign of r_s is negative, and the absolute value of r_s is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

Employing the above guidelines, the nondirectional alternative hypothesis $H_1: \rho_s \neq 0$ is supported at the .05 level, since the computed value $r_s = 1$ is equal to the tabled critical two-tailed value $r_{s_{.05}} = 1$. The directional alternative hypothesis $H_1: \rho_s > 0$ is supported at both the .05 and .01 levels, since the computed value $r_s = 1$ is a positive number that is equal to or greater than the tabled critical one-tailed values $r_{s_{.05}} = .90$ and $r_{s_{.01}} = 1$. The directional alternative hypothesis $H_1: \rho_s < 0$ is not supported, since the computed value $r_s = 1$ is a positive number.

When the **Pearson product-moment correlation coefficient** is employed to evaluate the same set of data (i.e., the ratio scores of subjects are correlated with one another), the nondirectional alternative hypothesis (i.e., $H_1: \rho \neq 0$) is also supported at only the .05 level, and the directional alternative hypothesis (i.e., $H_1: \rho > 0$) is supported at both the .05 and .01 levels. Thus, in this instance, the two correlation coefficients yield comparable results. (However, since **Pearson r** is the more powerful of the two correlational procedures, it is more likely to result in rejection of the null hypothesis at a given level of significance when applied to the same set of data.)

Test 29a: Test of significance for Spearman's rank-order correlation coefficient In the event a researcher does not have access to **Table A18**, Equation 29.2 which employs the t distribution, provides an alternative way of evaluating the null hypothesis $H_0: \rho_s = 0$. Most sources that recommend Equation 29.2 state that it provides a reasonably good approximation of the underlying sampling distribution when $n > 10$.

$$t = \frac{r_s \sqrt{n - 2}}{\sqrt{1 - r_s^2}} \quad (\text{Equation 29.2})$$

The t value computed with Equation 29.2 is evaluated with **Table A2 (Table of Student's t Distribution)** in the **Appendix**. The degrees of freedom employed are $df = n - 2$. Thus, in the case of Example 29.1, $df = 5 - 2 = 3$. For $df = 3$, the tabled critical two-tailed .05 and .01 values are $t_{.05} = 3.18$ and $t_{.01} = 5.84$, and the tabled critical one-tailed .05 and .01 values are $t_{.05} = 2.35$ and $t_{.01} = 4.54$. Since the sign of the t value computed with Equation 29.2 will always be the same as the sign of r_s , the guidelines described earlier in reference to **Table A18** for evaluating an r_s value can also be applied in evaluating the t value computed with Equation 29.2 (i.e., substitute t in place of r_s in the text of the guidelines for evaluating r_s).

Inspection of Equation 29.2 reveals that if the absolute value of r_s equals 1, the term $\sqrt{1 - r^2}$ will equal zero, thus rendering the equation insoluble (i.e., $t = [(1)\sqrt{5 - 2}] / \sqrt{1 - (1)^2} = ?$). Consequently, Equation 29.2 cannot be applied to Example 29.1.

Equation 29.3, which employs the normal distribution, is an alternative equation for evaluating the significance of r_s . When the sample size is large (approximately 200 or greater), Equation 29.3 will yield a result that is equivalent to that obtained with Equation 29.2.⁵

$$z = r_s \sqrt{n - 1} \quad (\text{Equation 29.3})$$

Although the sample size in Example 29.1 is well below the minimum size recommended

for Equation 29.3, the appropriate values will be substituted in the latter equation in order to demonstrate its application. Substituting the values $r_s = 1$ and $n = 5$ in Equation 29.3, the value $z = 2.00$ is computed.

$$z = (1)\sqrt{5 - 1} = 2$$

The computed value $z = 2.00$ is evaluated with **Table A1 (Table of the Normal Distribution)** in the **Appendix**. In the latter table, the tabled critical two-tailed .05 and .01 values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed .05 and .01 values are $z_{.05} = 1.65$ and $z_{.01} = 2.33$. Since the sign of the z value computed with Equation 29.3 will always be the same as the sign of r_s , the guidelines described earlier in reference to **Table A18** for evaluating an r_s value can also be applied in evaluating the z value computed with Equation 29.3 (i.e., substitute z in place of r_s in the text of the guidelines for evaluating r_s).

Employing the guidelines, the nondirectional alternative hypothesis $H_1: \rho_s \neq 0$ is supported at the .05 level, since the computed value $z = 2.00$ is greater than the tabled critical two-tailed value $z_{.05} = 1.96$. It is not, however, supported at the .01 level, since $z = 2.00$ is less than the tabled critical two-tailed value $z_{.01} = 2.58$.

The directional alternative hypothesis $H_1: \rho_s > 0$ is supported at the .05 level, since the computed value $z = 2.00$ is a positive number that is greater than the tabled critical one-tailed value $z_{.05} = 1.65$. It is not, however, supported at the .01 level, since $z = 2.00$ is less than the tabled critical one-tailed value $z_{.01} = 2.33$.

The directional alternative hypothesis $H_1: \rho < 0$ is not supported, since the computed value $z = 2.00$ is a positive number. In order for the alternative hypothesis $H_1: \rho_s < 0$ to be supported, the computed value of z must be a negative number (as well as the fact that the absolute value of z must be equal to or greater than the tabled critical one-tailed value at the prespecified level of significance). Note that the results obtained through use of Equation 29.3 are reasonably consistent with those that are obtained when **Table A18** is employed.⁶

A summary of the analysis of Example 29.1 follows: It can be concluded that there is a significant monotonic increasing/positive relationship between the number of ounces of sugar a ten-year-old child eats and the number of cavities in a child's mouth. This result can be summarized as follows (if it is assumed the nondirectional alternative hypothesis $H_1: \rho_s \neq 0$ is employed): $r_s = 1$, $p < .05$.

VI. Additional Analytical Procedures for Spearman's Rank-Order Correlation Coefficient and/or Related Tests

1. Tie correction for Spearman's rank-order correlation coefficient When one or more ties are present in a set of data, many sources recommend that the r_s value computed with Equation 29.1 be adjusted. The reason for this is that when ties are present, Equation 29.1 spuriously inflates the absolute value of r_s . In practice, most of the time that ties are present the effect on the value of r_s will be minimal (unless the number of ties is excessive). The tie correction procedure to be demonstrated in this section will employ the data summarized in **Table 29.2**. Assume that the data are for the same variables evaluated in Example 29.1, except for the fact that a different set of subjects is employed with $n = 10$.

Employing Equation 29.1, it is determined that the value of **Spearman's rho** without employing a tie correction is $r_s = .764$.

$$r_s = 1 - \frac{6(39)}{10[(10)^2 - 1]} = .764$$

Table 29.2 Data Employed with Tie Correction Procedure

Subject	X	R_X	Y	R_Y	$d = R_X - R_Y$	d^2
1	0	1.5	1	2	-.5	.25
2	0	1.5	0	1	.5	.25
3	2	3	2	3.5	-.5	.25
4	4	4	2	3.5	.5	.25
5	8	6	8	9.5	-3.5	12.25
6	8	6	8	9.5	-3.5	12.25
7	8	6	3	5	1	1
8	13	8	4	6	2	4
9	16	9.5	6	7	2.5	6.25
10	16	9.5	7	8	1.5	2.25
					$\Sigma d = 0$	$\Sigma d^2 = 39$

The tie correction will now be introduced. In the example under discussion there are $s = 3$ sets of ties involving the ranks of subjects' X scores (Subjects 1 and 2; Subjects 5, 6, and 7; Subjects 9 and 10), and $s = 2$ sets of ties involving the ranks of subjects' Y scores (Subjects 3 and 4; Subjects 5 and 6). Equation 29.8 is employed to compute the tie-corrected **Spearman's rank-order correlation coefficient**, which will be represented by the notation r_{S_c} . Note that the values Σx^2 and Σy^2 in Equation 29.8 are computed with Equations 29.6 and 29.7, and that Equations 29.6 and 29.7 are, respectively, based on the values T_X and T_Y , which are computed with Equations 29.4 and 29.5. In Equation 29.4, $t_{i(x)}$ represents the number of X scores that are tied for a given rank. In Equation 29.5, $t_{i(y)}$ represents the number of Y scores that are tied for a given rank. The notations $\sum_{i=1}^s (t_{i(x)}^3 - t_{i(x)})$ and $\sum_{i=1}^s (t_{i(y)}^3 - t_{i(y)})$ indicate that the following is done with respect to each of the variables: a) For each set of ties, the number of ties in the set is subtracted from the cube of the number of ties in that set; and b) The sum of all the values computed in part a) is obtained for that variable.

When the data from Table 29.2 are substituted in Equations 29.4–29.8, the tie-corrected value $r_{S_c} = .758$ is computed.

$$T_X = \sum_{i=1}^s (t_{i(x)}^3 - t_{i(x)}) = [(2)^3 - 2] + [(3)^3 - 3] + [(2)^3 - 2] = 36 \quad (\text{Equation 29.4})$$

$$T_Y = \sum_{i=1}^s (t_{i(y)}^3 - t_{i(y)}) = [(2)^3 - 2] + [(2)^3 - 2] = 12 \quad (\text{Equation 29.5})$$

$$\Sigma x^2 = \frac{n^3 - n - T_X}{12} = \frac{(10)^3 - 10 - 36}{12} = 79.5 \quad (\text{Equation 29.6})$$

$$\Sigma y^2 = \frac{n^3 - n - T_Y}{12} = \frac{(10)^3 - 10 - 12}{12} = 81.5 \quad (\text{Equation 29.7})$$

$$r_{S_c} = \frac{\Sigma x^2 + \Sigma y^2 - \Sigma d^2}{2\sqrt{\Sigma x^2 \Sigma y^2}} = \frac{79.5 + 81.5 - 39}{2\sqrt{(79.5)(81.5)}} = .758 \quad (\text{Equation 29.8})$$

Thus, by employing the tie correction, the value of **rho** is reduced from the uncorrected value of $r_S = .764$ to $r_{S_c} = .758$. As noted earlier, the correction is minimal.

2. Spearman's rank-order correlation coefficient as a special case of the Pearson product-moment correlation coefficient Although the procedure described in the previous section for dealing with ties is the one recommended in most sources, in actuality, an alternative and at times more computationally efficient procedure can be employed. In Section I it is noted that **Spearman's rank-order correlation coefficient** is a special case of the **Pearson product-moment correlation coefficient**. In point of fact, if the **Pearson product-moment correlation coefficient** is computed for the rank-orders in a set of interval/ratio data, the computed r value will be identical to the value computed for r_s with Equation 29.1. This is demonstrated below for Example 29.1, where Equation 28.1 (the equation for computing the **Pearson product-moment correlation coefficient**) is employed to compute the value $r = r_s = 1$. Table 29.3 summarizes the values that are substituted in Equation 28.1. Note that the ranks R_X and R_Y employed in Table 29.1 are used in Table 29.3 to represent the scores on the X and Y variables.⁷

$$r = r_s = \frac{55 - \frac{(15)(15)}{5}}{\sqrt{\left[55 - \frac{(15)^2}{10}\right]\left[55 - \frac{(15)^2}{10}\right]}} = 1$$

Table 29.3 Summary of Data for Example 29.1 for Evaluation with Equation 28.1

Subject	X	X^2	Y	Y^2	XY
1	5	25	5	25	25
2	1	1	1	1	1
3	2	4	2	4	4
4	4	16	4	16	16
5	3	9	3	9	9
<hr/>					
	$\Sigma X = 15$	$\Sigma X^2 = 55$	$\Sigma Y = 15$	$\Sigma Y^2 = 55$	$\Sigma XY = 55$

Table 29.4 Summary of Data in Table 29.2 for Evaluation with Equation 28.1

Subject	X	X^2	Y	Y^2	XY
1	1.5	2.25	2	4	3
2	1.5	2.25	1	1	1.5
3	3	9	3.5	12.25	10.5
4	4	16	3.5	12.25	14
5	6	36	9.5	90.25	57
6	6	36	9.5	90.25	57
7	6	36	5	25	30
8	8	64	6	36	48
9	9.5	90.25	7	49	66.5
10	9.5	90.25	8	64	76
<hr/>					
	$\Sigma X = 55$	$\Sigma X^2 = 382$	$\Sigma Y = 55$	$\Sigma Y^2 = 384$	$\Sigma XY = 363.5$

When there are no ties present in the data, Equations 29.1 and 28.1 will always yield the identical value for r_s . However, anytime there is at least one set of ties, the values yielded by the two equations will not be identical. In point of fact, Howell (1992, 1997) notes that when ties are present in the data, the r_s value computed with Equation 28.1 will be equivalent to the tie-corrected value r_{sc} computed with Equation 29.8. When there are no ties present in the data, it is clearly more efficient to employ Equation 29.1 than it is to employ Equation 28.1. However,

when ties are present, it can be argued that use of Equation 28.1 is more computationally efficient than Equation 29.8. To demonstrate the equivalency of Equation 28.1 and Equation 29.8, Equation 28.1 is employed below with the rank-orders in Table 29.2. Table 29.4 summarizes the values that are substituted in Equation 28.1. The value $r = .758$ obtained with Equation 28.1 is identical to the value $r_{s_c} = .758$ obtained with Equation 29.8.

$$r = \frac{363.5 - \frac{(55)(55)}{10}}{\sqrt{\left[382 - \frac{(55)^2}{10}\right]\left[384 - \frac{(55)^2}{10}\right]}} = .758$$

3. Regression analysis and Spearman's rank-order correlation coefficient When **Spearman's rank-order correlation coefficient** is computed for a set of data, a researcher may also want to derive the mathematical function that best allows one to predict a subject's score on one variable through use of the subject's score on the second variable. To do this requires the use of regression analysis which, as noted in Section VI of the **Pearson product-moment correlation coefficient**, is a general term that describes statistical procedures which determine the mathematical function that best describes the relationship between two or more variables. One type of regression analysis that falls within the general category of **nonparametric regression analysis** is referred to as **monotonic regression analysis**. The latter type of analysis is based on the fact that if two variables (which are represented by interval/ratio data) are monotonically related to one another, the rankings on the variables will be linearly related to one another. This can be illustrated in reference to Example 29.1 through use of Figure 29.2. Whereas Figure 28.1 (in Section VI of the **Pearson product-moment correlation coefficient**) represents a scatterplot of the five pairs of ratio scores for Examples 28.1/29.1, Figure 29.2 is a scatterplot of the five pairs of ranks on the two variables. Note that the scatterplot is such that one can draw a positively sloped straight line which passes through all of the data points. The only time all of the data points will fall on the regression line is when the absolute value of the correlation between the two variables equals 1. Although some data points may fall on the line when an imperfect monotonic relationship is present, the others will not. The stronger the monotonic relationship, the closer the proximity of the data points to the line.

As is noted in Section VI of the **Pearson product-moment correlation coefficient**, the most commonly employed method of regression analysis is the method of least squares (which is a linear regression procedure that derives the straight line which provides the best fit for a set of data). Although visual inspection of Figures 28.1 and 29.2 suggests a strong monotonic increasing relationship between the two variables (i.e., an increase in the number of ounces of sugar consumed is associated with an increase in the number of cavities), it does not allow one to precisely determine whether the function that best describes the relationship is a straight line or a monotonic curve. In order to determine the latter, it is necessary to contrast the predictive accuracy of the method of least squares with some alternative form of regression analysis. Conover (1980, 1999), who provides a bibliography on the general subject of monotonic regression analysis, describes its application in deriving a curve for a set of rank-ordered data. Marascuilo and McSweeney (1977) and Sprent (1989, 1993) also discuss the subject of monotonic regression analysis. In addition to sources on nonparametric statistics that discuss monotonic regression, many books on correlation and regression describe procedures for deriving different types of curvilinear functions. Daniel (1990) discusses a number of different approaches to nonparametric regression analysis, which derive the straight line that best describes the relationship between the interval/ratio scores on the two variables. These latter types of regression analysis (which employ the median instead of the mean as a reference point) are recommended when there is reason to

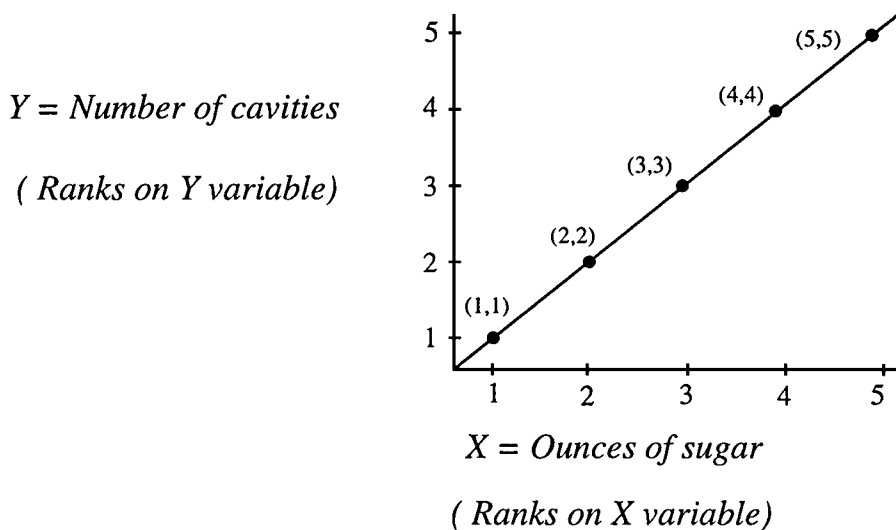


Figure 29.2 Scatterplot of Ranks for Example 29.1

believe that one or more of the assumptions underlying the method of least squares are saliently violated. Among those procedures Daniel (1990) describes are the **Brown-Mood method** (Brown and Mood (1951), and Mood (1950)), and a methodology developed by Theil (1950). Daniel (1990) also provides a comprehensive bibliography on the subject of nonparametric regression analysis.

4. Partial rank correlation The computation of a **partial correlation coefficient**, described in Section IX of the **Pearson product-moment correlation coefficient**, can be extended to **Spearman's rank-order correlation coefficient**. Thus, when the rank-orders for three variables are evaluated, Equation 28.72 can be employed to compute a **partial correlation coefficient** for **Spearman's rho** (employing the relevant r_s values in the equation). Conover (1980, 1999) and Daniel (1990) discuss the computation of a **partial correlation coefficient** in reference to **Spearman's rho**.

5. Use of Fisher's z_r transformation with Spearman's rank-order correlation coefficient Zar (1999) notes that when $n \geq 10$ and $\rho_s < .9$ (the value of which is estimated by r_s), the equations and procedures employing **Fisher's z_r transformation** that are described in reference to the **Pearson product-moment correlation coefficient** can also be employed for **Spearman's rho**. The latter procedures involve testing various hypotheses about a correlation coefficient, computing confidence intervals, and computing power (all of which are described in Section VI of the **Pearson product-moment correlation coefficient**). Zar (1999) notes, however, that when the element $1/(n - 3)$ (where $\sqrt{1/(n - 3)}$ represents the standard error of **Fisher's z_r**) appears in an equation, it should be replaced by the value $1.060/(n - 3)$ when the computations are in reference to **Spearman's rho** (e.g., Equation 28.20 should be in the form $z = (z_r - z_{r_0})/\sqrt{1.060/(n - 3)}$ when evaluating the same hypothesis for **Spearman's rho**).

VII. Additional Discussion of Spearman's Rank-Order Correlation Coefficient

1. The relationship between Spearman's rank-order correlation coefficient, Kendall's coefficient of concordance, and the Friedman two-way analysis of variance by ranks

Kendall's coefficient of concordance (Test 31), which is discussed later in the book, is a measure of association that allows a researcher to evaluate the degree of agreement between m sets of ranks on n subjects/objects. In point of fact, **Kendall's coefficient of concordance** is linearly related to **Spearman's rank-order correlation coefficient**.⁸ The underlying statistical model upon which **Kendall's coefficient of concordance** is based is identical to the model for the **Friedman two-way analysis of variance by ranks (Test 25)**. As a result of this, the **Friedman two-way analysis of variance by ranks** can be employed to determine whether the value of the **coefficient of concordance** is significant. In point of fact, the **Friedman two-way analysis of variance by ranks** can also be used to determine whether the value of **Spearman's rho** is significant. This will be illustrated with Example 29.2, which represents a type of problem that is commonly evaluated with **Spearman's rank-order correlation coefficient** (as well as **Kendall's coefficient of concordance** when there are more than two sets of ranks). In Example 29.2, $n = 10$ films (i.e., objects/subjects) are rank-ordered by $m = 2$ judges, and a determination is made with respect to the degree of agreement among the rankings of the judges.

Example 29.2 *In order to determine whether two critics agree with one another in their evaluation of movies, a newspaper editor asks the two critics to rank-order ten movies (assigning a rank of 1 to the best movie, a rank of 2 to the next best movie, etc.). Table 29.5 summarizes the data for the study. Is there a significant association between the two sets of ranks?*

Table 29.5 Summary of Data for Example 29.2

Movie	Critic 1	Critic 2	$d = R_x - R_y$	d^2
	R_x	R_y		
1	7	10	-3	9
2	1	2	-1	1
3	8	6	2	4
4	10	8	2	4
5	9	7	2	4
6	6	4	2	4
7	5	9	-4	16
8	2.5	3	-.5	.25
9	2.5	1	1.5	2.25
10	4	5	-1	1
			$\Sigma d = 0$	$\Sigma d^2 = 45.5$

Note that in Table 29.5 each of the $n = 10$ rows represents one of the ten movies, instead of representing $n = 10$ subjects (as is the case in Example 29.1). The ranks of Critic 1 are represented in the column labelled R_x , and the ranks of Critic 2 are represented in the column labelled R_y . Note that Critic 1 places Movies 8 and 9 in a tie for the second best movie. Thus (employing the protocol for tied ranks described in Section IV of the **Mann-Whitney U test**), the two ranks involved (2 and 3) are averaged $((2 + 3)/2 = 2.5)$, and each of the movies is assigned the average rank of 2.5.

Employing Equation 29.1, the value $r_s = .724$ is computed. The tie-corrected value $r_{s_c} = .723$ (for which the calculations are not shown) is almost identical.

$$r = 1 - \frac{(6)(45.5)}{10[(10)^2 - 1]} = .724$$

Employing **Table A18**, it is determined that for $n = 10$, the tabled critical two-tailed .05 and .01 values are $r_{S_{.05}} = .648$ and $r_{S_{.01}} = .794$, and the tabled critical one-tailed .05 and .01 values are $r_{S_{.05}} = .564$ and $r_{S_{.01}} = .745$. Employing the aforementioned critical values, the nondirectional alternative hypothesis $H_1: \rho_S \neq 0$ and the directional alternative hypothesis $H_1: \rho_S > 0$ are supported at the .05 level, since the computed value $r_S = .724$ is greater than the tabled critical two-tailed value $r_{S_{.05}} = .648$ and the tabled critical one-tailed value $r_{S_{.05}} = .564$. The alternative hypotheses are not supported at the .01 level, since $r_S = .724$ is less than the tabled critical two-tailed value $r_{S_{.01}} = .794$ and the tabled critical one-tailed value $r_{S_{.01}} = .745$.

If Equation 29.2 is employed to evaluate the null hypothesis $H_0: \rho_S = 0$, the value $t = 2.97$ is computed.

$$t = \frac{(.724)\sqrt{10 - 2}}{\sqrt{1 - (.724)^2}} = 2.97$$

Employing **Table A2**, it is determined that for $df = 10 - 2 = 8$, the tabled critical two-tailed .05 and .01 values are $t_{.05} = 2.31$ and $t_{.01} = 3.36$, and the tabled critical one-tailed .05 and .01 values are $t_{.05} = 1.86$ and $t_{.01} = 2.90$. Employing the aforementioned critical values, the nondirectional alternative hypothesis $H_1: \rho_S \neq 0$ is supported at the .05 level, since the computed value $t = 2.97$ is greater than the tabled critical two-tailed value $t_{.05} = 2.31$. It is not supported at the .01 level, since $t = 2.97$ is less than $t_{.01} = 3.36$. The directional alternative hypothesis $H_1: \rho_S > 0$ is supported at both the .05 and .01 levels, since the computed value $t = 2.97$ is a positive number (since $r_S = .724$ is a positive number) that is greater than the tabled critical one-tailed values $t_{.05} = 1.86$ and $t_{.01} = 2.90$.

If Equation 29.3 is employed to evaluate the null hypothesis $H_0: \rho_S = 0$, the value $z = 2.17$ is computed.

$$z = (.724)\sqrt{10 - 1} = 2.17$$

Employing **Table A1**, it is determined that the computed value $z = 2.17$ is greater than the tabled critical two-tailed value $z_{.05} = 1.96$ and the tabled critical one-tailed value $z_{.05} = 1.65$, but less than the tabled critical two-tailed value $z_{.01} = 2.58$ and the tabled critical one-tailed value $z_{.01} = 2.33$. Thus, both the nondirectional alternative hypothesis $H_1: \rho_S \neq 0$ and the directional alternative hypothesis $H_1: \rho_S > 0$ are supported at the .05 level, but not at the .01 level. Note that identical conclusions are reached with **Table A18** and Equation 29.3, but the latter conclusions are not identical to those obtained with Equation 29.2 (where the directional alternative hypothesis $H_1: \rho_S > 0$ is also supported at the .01 level). As noted in Section V, the conclusions based on use of **Table A18**, Equation 29.2, and Equation 29.3 will not always be in total agreement.

It is noted earlier in this section that the **Friedman two-way analysis of variance by ranks** can be employed to determine whether the value of **Spearman's rho** is significant. This will now be illustrated in reference to Example 29.2. The data for Example 29.2 are rearranged in **Table 29.6** to conform to the test model for the **Friedman two-way analysis of variance by ranks**. Note that the rows and columns employed in **Table 29.5** are reversed in **Table 29.6**. When **Table 29.6** is employed within the framework of the **Friedman test** model, the two critics represent $n = 2$ subjects, and the 10 ranks represent $k = 10$ levels of a within-subjects/repeated-measures independent variable.

Table 29.6 Data for Example 29.2 Formatted for Analysis with the Friedman Two-Way Analysis of Variance by Ranks

Movie	1	2	3	4	5	6	7	8	9	10
Critic 1	7	1	8	10	9	6	5	2.5	2.5	4
Critic 2	10	2	6	8	7	4	9	3	1	5
ΣR_j	17	3	14	18	16	10	14	5.5	3.5	9
$(\Sigma R_j)^2$	289	9	196	324	256	100	196	30.25	12.25	81

From the summary information in Table 29.6, the value $\sum_{j=1}^k (\Sigma R_j)^2 = 1493.5$ is computed.

$$\sum_{j=1}^k (\Sigma R_j)^2 = 289 + 9 + 196 + 324 + 256 + 100 + 196 + 30.25 + 12.25 + 81 = 1493.5$$

Employing the above value, along with the other appropriate values in Equation 25.1 (the equation for the **Friedman two-way analysis of variance by ranks**), the value $\chi_r^2 = 15.46$ is computed.⁹

$$\begin{aligned}\chi_r^2 &= \frac{12}{nk(k+1)} \sum_{j=1}^k (\Sigma R_j)^2 - 3n(k+1) \\ &= \left[\frac{12}{(2)(10)(10+1)} \right] [1493.5] - (3)(2)(10+1) = 15.46\end{aligned}$$

The value $\chi_r^2 = 15.46$ is evaluated with Table A4 (Table of the Chi-Square Distribution) in the Appendix. For $df = k - 1 = 10 - 1 = 9$, the tabled critical two-tailed .05 and .01 values are $\chi_{.05}^2 = 16.92$ and $\chi_{.01}^2 = 21.67$, and the tabled critical one-tailed .05 and .01 values are $\chi_{.05}^2 = 14.68$ and $\chi_{.01}^2 = 19.50$ (the latter value is interpolated).¹⁰ Employing the aforementioned critical values, the null hypothesis for the **Friedman two-way analysis of variance by ranks** ($H_0: \theta_1 = \theta_2 = \dots = \theta_{10}$) can be rejected at the .05 level, but only if a one-tailed analysis is conducted (since $\chi_r^2 = 15.46$ is greater than the tabled critical one-tailed value $\chi_{.05}^2 = 14.68$).¹¹ The result falls short of being significant at the .05 level for a two-tailed analysis, since $\chi_r^2 = 15.46$ is less than the tabled critical two-tailed value $\chi_{.05}^2 = 16.92$. Rejection of the null hypothesis for the **Friedman two-way analysis of variance by ranks** is commensurate with rejection of the null hypothesis $H_0: \rho_S = 0$ for **Spearman's rank-order correlation coefficient**. In actuality, the result derived employing the **Friedman two-way analysis of variance by ranks** is similar, but not identical, to the analysis of **Spearman's rho** with Table A18, Equation 29.2, and Equation 29.3 (which, as noted earlier, are not in themselves in total agreement). The slight discrepancy between the results of the **Friedman test** and the more commonly employed methods for assessing the significance of **Spearman's rho** can be attributed to the fact that the test statistics based on the t , normal, and chi-square distributions are large sample approximations, which in the case of Example 29.2 are employed with a small sample size. It was also noted earlier, that the values in Table A18 are approximations of the exact values in the underlying sampling distribution.

2. Power efficiency of Spearman's rank-order correlation coefficient Daniel (1990) and Siegel and Castellan (1988) note that (for large sample sizes) the **asymptotic relative efficiency** (which is discussed in Section VII of the **Wilcoxon signed-ranks test (Test 6)**) of **Spearman's rank-order correlation coefficient** relative to the **Pearson product-moment correlation coefficient** is approximately .91 (when the assumptions underlying the latter test are met).

3. Brief discussion of Kendall's Tau: An alternative measure of association for two sets of ranks **Kendall's tau (Test 30)** is an alternative measure of association that can be employed to evaluate two sets of ranks. Although **Spearman's rho** and **Kendall's tau** can be employed to measure the degree of association for the same set of data, **Spearman's rho** is the more commonly described of the two measures (primarily because it requires fewer computations). A comparative discussion of **Spearman's rho** and **Kendall's tau** can be found in Section I of the latter test.

4. Weighted rank/top-down correlation There may be occasions when a researcher's primary interest is with respect to the correlation among the most extreme scores in a set of data (i.e., that group of scores that comprise the highest and lowest values for both variables). The latter can be achieved through use of a procedure (developed by Salama and Quade (1981) and Quade and Salama (1992)) that weights scores such that the more extreme a score is, the greater its weight in determining the correlation coefficient. The latter procedure, which is referred to as **weighted rank correlation** or **top-down correlation** (Iman and Conover (1985, 1987)) is described in Zar (1999, pp. 398–401).

VIII. Additional Examples Illustrating the Use of Spearman's Rank-Order Correlation Coefficient

If a researcher elects to rank-order the scores of subjects in any of the examples for which the **Pearson product-moment correlation coefficient** is employed, a value can be computed for **Spearman's rank-order correlation coefficient**. Thus, as is the case for Example 28.1, the data for Examples 28.2 and 28.3 can be rank-ordered and evaluated with **Spearman's rho**. Since the rankings for the latter two examples are identical to the rankings for Example 29.1, all three examples yield the identical result. Since **Kendall's tau** and **Spearman's rho** can be employed to evaluate the same data, Example 30.1, as well as the data set presented in [Table 30.4](#), can also be evaluated with **Spearman's rho**.

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Endnotes

1. It should be noted that although the scores of subjects in Example 29.1 are ratio data, in most instances when **Spearman's rank-order correlation coefficient** is employed it is more likely that the original data for both variables are in a rank-order format. As is noted in Section I, conversion of ratio data to a rank-order format (which is done in Section IV with respect to Example 29.1) is most likely to occur when a researcher has reason to believe that one or more of the underlying assumptions of the **Pearson product-moment correlation coefficient** are saliently violated. Example 29.2 in Section VI represents a study involving two variables that are originally in a rank-order format for which **Spearman's rho** is computed.
2. Some sources employ the following statements as the null hypothesis and the nondirectional alternative hypothesis for **Spearman's rank-order correlation coefficient**: **Null hypothesis**: H_0 : Variables X and Y are independent of one another; **Nondirectional alternative hypothesis**: H_1 : Variables X and Y are not independent of one another.

It is, in fact, true that if in the underlying population the two variables are independent, the value of ρ_s will equal zero. However, the fact that $\rho_s = 0$, in and of itself,

does not ensure that the variables are independent of one another. Thus, it is conceivable that in a population in which the correlation between X and Y is $\rho_s = 0$, a nonmonotonic curvilinear function can be employed to describe the relationship between the variables.

3. Daniel (1990) notes that the computed value of r_s is not an unbiased estimate of ρ_s .
4. The reader may find slight discrepancies in the critical values listed for **Spearman's rho** in the tables published in different books. The differences are due to the fact that separate tables derived by Olds (1938, 1949) and Zar (1972), which are not identical, are employed in different sources. Howell (1992, 1997) notes that the tabled critical values noted in various sources are approximations and not exact values.
5. The minimum sample size for which Equation 29.3 is recommended varies depending upon which source one consults. Some sources recommend the use of Equation 29.3 for values as low as $n = 25$, whereas others state that n should equal at least 100.
6. The results obtained through use of **Table A18**, Equation 29.2, and Equation 29.3 will not always be in total agreement with one another. In instances where the different methods for evaluating significance do not agree, there will usually not be a major discrepancy between them. In the final analysis, the larger the sample size the more likely it is that the methods will be consistent with one another.
7. The following will always be true when Equation 28.1 is employed in computing **Pearson r** (and r_s), and the rank-orders are employed to represent the scores on the X and Y variables: $\Sigma X = \Sigma Y$ and $\Sigma X^2 = \Sigma Y^2$ (however, the latter will only be true if there are no ties).
8. The relationship between **Spearman's rank-order correlation coefficient** and **Kendall's coefficient of concordance** is discussed in greater detail in Section VII of the latter test. In the latter discussion, it is noted that although when there are two sets of ranks the values computed for **Spearman's rho** and **Kendall's coefficient of concordance** will not be identical, one value can be converted into the other through use of Equation 31.7.
9. If the tie correction for the **Friedman two-way analysis of variance by ranks** is employed, the computed value of χ_r^2 will be slightly higher.
10. The tabled critical two-tailed .05 and .01 chi-square values represent the chi-square values at the 95th and 99th percentiles, and the tabled critical one-tailed .05 and .01 chi-square values represent the chi-square values at the 90th and 98th percentiles.
11. In the discussion of the **Friedman two-way analysis of variance by ranks**, it is assumed that a nondirectional analysis is always conducted for the latter test. A directional/one-tailed analysis is used here in order to employ probability values that are comparable to the one-tailed values employed in evaluating **Spearman's rho**. Within the **Friedman test model**, when $k = 10$, the usage of the term one-tailed analysis is really not meaningful. For a clarification of this issue (i.e., conducting a directional analysis when $k > 3$), the reader should read the discussion on the directionality of the **chi-square goodness-of-fit test (Test 8)** in Section VII of the latter test (which can be generalized to the **Friedman test**).

Test 30

Kendall's Tau (Nonparametric Measure of Association/Correlation Employed with Ordinal Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Kendall's tau is one of a number of measures of correlation or association discussed in this book. Measures of correlation are not inferential statistical tests, but are, instead, descriptive statistical measures that represent the degree of relationship between two or more variables. Upon computing a measure of correlation, it is common practice to employ one or more inferential statistical tests in order to evaluate one or more hypotheses concerning the correlation coefficient. The hypothesis stated below is the most commonly evaluated hypothesis for **Kendall's tau**.

Hypothesis evaluated with test In the underlying population represented by a sample, is the correlation between subjects' scores on two variables some value other than zero? The latter hypothesis can also be stated in the following form: In the underlying population represented by the sample, is there a significant **monotonic** relationship between the two variables?¹ It is important to note that the nature of the relationship described by **Kendall's tau** is based on an analysis of two sets of ranks.

Relevant background information on test Prior to reading the material in this section the reader should review the general discussion of correlation in Section I of the **Pearson product-moment correlation coefficient (Test 28)**, and the material in Section I of **Spearman's rank-order correlation coefficient (Test 29)** (which also evaluates whether a monotonic relationship exists between two sets of ranks). Developed by Kendall (1938), **tau** is a bivariate measure of correlation/association that is employed with rank-order data. The population parameter estimated by the correlation coefficient will be represented by the notation τ (which is the lower case Greek letter **tau**). The sample statistic computed to estimate the value of τ will be represented by the notation $\tilde{\tau}$. As is the case with **Spearman's rank-order correlation coefficient**, **Kendall's tau** can be employed to evaluate data in which a researcher has scores for n subjects/objects on two variables (designated as the X and Y variables), both of which are rank-ordered. **Kendall's tau** is also commonly employed to evaluate the degree of agreement between the rankings of $m = 2$ judges for n subjects/objects.

As is the case with **Spearman's rho**, the range of possible values **Kendall's tau** can assume is defined by the limits -1 to $+1$ (i.e., $-1 \leq \tilde{\tau} \leq +1$). Although **Kendall's tau** and **Spearman's rho** share certain properties in common with one another, they employ a different logic with respect to how they evaluate the degree of association between two variables. **Kendall's tau** measures the degree of agreement between two sets of ranks with respect to the relative ordering of all possible pairs of subjects/objects. One set of ranks represents the ranks on the X variable, and the other set represents the ranks on the Y variable. Specifically, assume data are in the form of the following two pairs of observations expressed in a rank-order format: a) (R_{X_i}, R_{Y_i}) (which,

respectively, represent the ranks on Variables X and Y for the i^{th} subject/object); and b) (R_{X_j}, R_{Y_j}) (which, respectively, represent the ranks on Variables X and Y for the j^{th} subject/object). If the sign/direction of the difference $(R_{X_i} - R_{X_j})$ is the same as the sign/direction of the difference $(R_{Y_i} - R_{Y_j})$, a pair of ranks is said to be **concordant** (i.e., in agreement). If the sign/direction of the difference $(R_{X_i} - R_{X_j})$ is not the same as the sign/direction of the difference $(R_{Y_i} - R_{Y_j})$, a pair of ranks is said to be **discordant** (i.e., disagree). If $(R_{X_i} - R_{X_j})$ and/or $(R_{Y_i} - R_{Y_j})$ result in the value zero, a pair of ranks is neither concordant or discordant (and is conceptualized within the framework of a tie which is discussed in Section VI). **Kendall's tau** is a proportion that represents the difference between the proportion of concordant pairs of ranks less the proportion of discordant pairs of ranks. The computed value of **tau** will equal +1 when there is complete agreement among the rankings (i.e., all of the pairs of ranks are concordant), and will equal -1 when there is complete disagreement among the rankings (i.e., all of the pairs of ranks are discordant).

As a result of the different logic involved in computing **Kendall's tau** and **Spearman's rho**, the two measures have different underlying scales and, because of this, it is not possible to determine the exact value of one measure if the value of the other measure is known. As a general rule, however, the computed absolute value of $\tilde{\tau}$ will always be less than the computed absolute value of r_s for a set of data and, as the sample size increases, the ratio $\tilde{\tau}/r_s$ approaches the value .67.² Siegel and Castellan (1988) note the following inequality can be employed to describe the relationship between r_s and $\tilde{\tau}$: $-1 \leq (3\tilde{\tau} - 2r_s) \leq 1$.

In spite of the differences between **Kendall's tau** and **Spearman's rho**, the two statistics employ the same amount of information and, because of this, are equally likely to detect a significant effect in a population. Thus, although for the same set of data different values will be computed for r_s and $\tilde{\tau}$ (unless, as noted in Endnote 2, the correlation between the two variables is +1 or -1), the two measures will essentially result in the same conclusions with respect to whether or not the underlying population correlation equals zero. The comparability of $\tilde{\tau}$ and r_s is discussed in more detail in Section V.

In contrast to **Kendall's tau**, **Spearman's rho** is more commonly discussed in statistics books as a bivariate measure of correlation for ranked data. Two reasons for this are as follows: a) The computations required for computing **tau** are more tedious than those required for computing **rho**; and b) When a sample is derived from a bivariate normal distribution (which is discussed in Section I of the **Pearson product-moment correlation coefficient**), the computed value r_s will generally provide a reasonably good approximation of **Pearson r** , whereas the value of $\tilde{\tau}$ will not. Since r_s provides a good estimate of r , r_s^2 can be employed to represent the **coefficient of determination** (i.e., a measure of the proportion of variability on one variable that can be accounted for by variability on the other variable).³ One commonly cited advantage of **tau** over **rho** is that $\tilde{\tau}$ is an unbiased estimate of the population parameter τ , whereas the value computed for r_s is not an unbiased estimate of the population parameter ρ_s . Lindeman *et al.* (1980) note another advantage of **tau** is that unlike **rho**, the sampling distribution of **tau** approaches normality very quickly. Because of this, the normal distribution provides a good approximation of the exact sampling distribution of **tau** for small sample sizes. In contrast, a large sample size is required in order to employ the normal distribution to approximate the exact sampling distribution of **rho**.

II. Example

Example 30.1 *Two psychiatrists, Dr. X and Dr. Y, rank-order ten patients with respect to their level of psychological disturbance (assigning a rank of 1 to the least disturbed patient and a rank*

of 10 to the most disturbed patient). The rankings of the two psychiatrists (along with additional information that allows the value of **Spearman's rho** to be computed for the same set of data) are presented in [Table 30.1](#). Is there a significant correlation between the rank-orders assigned to the patients by the two doctors?

III. Null versus Alternative Hypotheses

Upon computing **Kendall's tau**, it is common practice to determine whether the obtained absolute value of the correlation coefficient is large enough to allow a researcher to conclude that the underlying population correlation coefficient between the two variables is some value other than zero. Section V describes how the latter hypothesis, which is stated below, can be evaluated through use of tables of critical $\tilde{\tau}$ values or through use of an inferential statistical test that is based on the normal distribution.

Null hypothesis $H_0: \tau = 0$

(In the underlying population the sample represents, the correlation between the ranks of subjects on Variable *X* and Variable *Y* equals 0.)

Alternative hypothesis $H_1: \tau \neq 0$

(In the underlying population the sample represents, the correlation between the ranks of subjects on Variable *X* and Variable *Y* equals some value other than 0. This is a **nondirectional alternative hypothesis**, and it is evaluated with a **two-tailed test**. Either a significant positive $\tilde{\tau}$ value or a significant negative $\tilde{\tau}$ value will provide support for this alternative hypothesis. In order to be significant, the obtained absolute value of $\tilde{\tau}$ must be equal to or greater than the tabled critical two-tailed $\tilde{\tau}$ value at the prespecified level of significance.)

or

$H_1: \tau > 0$

(In the underlying population the sample represents, the correlation between the ranks of subjects on Variable *X* and Variable *Y* equals some value greater than 0. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. Only a significant positive $\tilde{\tau}$ value will provide support for this alternative hypothesis. In order to be significant (in addition to the requirement of a positive $\tilde{\tau}$ value), the obtained absolute value of $\tilde{\tau}$ must be equal to or greater than the tabled critical one-tailed $\tilde{\tau}$ value at the prespecified level of significance.)

or

$H_1: \tau < 0$

(In the underlying population the sample represents, the correlation between the ranks of subjects on Variable *X* and Variable *Y* equals some value less than 0. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. Only a significant negative $\tilde{\tau}$ value will provide support for this alternative hypothesis. In order to be significant (in addition to the requirement of a negative $\tilde{\tau}$ value), the obtained absolute value of $\tilde{\tau}$ must be equal to or greater than the tabled critical one-tailed $\tilde{\tau}$ value at the prespecified level of significance.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis is rejected.⁴

IV. Test Computations

The data for Example 30.1 are summarized in [Table 30.1](#). Although the last two columns of [Table 30.1](#) are not necessary to compute the value of **Kendall's tau**, they are included to allow for the computation of **Spearman's rank-order correlation coefficient** for the same set of data (which is done in Section V).

Table 30.1 Data for Example 30.1

Patient	Rankings of Dr. X R_{X_i}	Rankings of Dr. Y R_{Y_i}	$d_i = R_{X_i} - R_{Y_i}$	d_i^2
1	7	10	-3	9
2	1	2	-1	1
3	8	6	2	4
4	10	8	2	4
5	9	7	2	4
6	6	4	2	4
7	5	9	-4	16
8	3	3	0	0
9	2	1	1	1
10	4	5	-1	1
			$\Sigma d_i = 0$	$\Sigma d_i^2 = 44$

Equation 30.1 is employed to compute the value of **Kendall's tau**

$$\hat{\tau} = \frac{n_C - n_D}{\left[\frac{n(n-1)}{2} \right]} \quad (\text{Equation 30.1})$$

Where: n_C is the number of concordant pairs of ranks
 n_D is the number of discordant pairs of ranks
 $[n(n-1)]/2$ is the total number of possible pairs of ranks

In order to employ Equation 30.1 to compute the value of **Kendall's tau**, it is necessary to determine the number of concordant versus discordant pairs of ranks. In order to do this, the data are recorded in the format employed in [Table 30.2](#).

The first row of [Table 30.2](#) consists of the identification number of each subject. The order in which subjects are listed is based on their rank-order on the X variable (i.e., R_{X_i}). The latter set of ranks are recorded in the second row of the table. The third row lists each subject's rank-order on the Y variable (i.e., R_{Y_i}). Inspection of [Table 30.2](#) reveals that no ties are present in the data on either the X or the Y variable. The protocol to be described in this section assumes that there are no ties. The protocol for handling ties is described in Section VI. The portion of [Table 30.2](#) that lies below the double line consists of cells in which there is either an entry of **C** or **D** (except for the number value to the left of each row). This part of the table provides information with regard to the concordant versus discordant pairs of observations for the two sets of ranks. Specifically, in each of the rows of the table that fall below the double line, the number to the left of a row is the R_{Y_i} value (i.e., rank on the Y variable) of the subject represented by the column

in which that value appears. Within each row, the R_{Y_i} value is compared with those R_{Y_j} values that fall in the columns to its right. In any instance where an R_{Y_j} value in a column is larger than the R_{Y_i} value for the row, a **C** is recorded in the cell that is the intersection of that row and column. In any instance where an R_{Y_j} value in a column is smaller than the R_{Y_i} value for the row, a **D** is recorded in the cell that is the intersection of that row and column. The presence of a **C** in a cell indicates a **concordant** pair of observations, since the ordering of the ranks on both the X and Y variables for that pair of observations is in the same direction. The presence of a **D** in a cell indicates a **discordant** pair of observations, since the ordering of the ranks on both the X and Y variables for that pair of observations is in the opposite direction.

Table 30.2 Computational Table for Kendall's Tau

Subject	2	9	8	10	7	6	1	3	5	4	ΣC	ΣD
R_{X_i}	1	2	3	4	5	6	7	8	9	10		
R_{Y_i}	2	1	3	5	9	4	10	6	7	8		
	2	D	C	C	C	C	C	C	C	C	8	1
		1	C	C	C	C	C	C	C	C	8	0
			3	C	C	C	C	C	C	C	7	0
				5	C	D	C	C	C	C	5	1
					9	D	C	D	D	D	1	4
						4	C	C	C	C	4	0
							10	D	D	D	0	3
								6	C	C	2	0
									7	C	1	0
										8	0	0
$\Sigma \Sigma C = n_C = 36$ $\Sigma \Sigma D = n_D = 9$												

The last two columns of [Table 30.2](#) contain the number of concordant (ΣC) versus discordant (ΣD) pairs of observations in each row. The value $\Sigma \Sigma C = n_C = 36$ in the last row of [Table 30.2](#) is the sum of the column labelled ΣC . The value $\Sigma \Sigma C = n_C = 36$ represents the total number of **C** entries in the table, which is the total number of concordant pairs of observations in the data. The value $\Sigma \Sigma D = n_D = 9$ is the sum of the column labelled ΣD . The value $\Sigma \Sigma D = n_D = 9$ represents the total number of **D** entries in the table, which is the total number of discordant pairs of observations in the data (which are also referred to as **inversions**).

Substituting the values $n_C = 36$, $n_D = 9$, and $n = 10$ in Equation 30.1, the value $\tilde{\tau} = .60$ is computed.

$$\tilde{\tau} = \frac{36 - 9}{\left[\frac{10(10 - 1)}{2} \right]} = .60$$

The reader should note the following with respect to the sign of $\tilde{\tau}$: a) When $n_C > n_D$, the sign of $\tilde{\tau}$ will be positive; b) When $n_D > n_C$, the sign of $\tilde{\tau}$ will be negative; and c) When $n_C = n_D$, $\tilde{\tau}$ will equal zero.

Some sources employ the notation S to represent the value $(n_C - n_D)$ in the numerator of Equation 30.1. For Example 30.1, $S = 36 - 9 = 27$. If the value S is employed, the value of $\tilde{\tau}$ can be computed with Equation 30.2.

$$\tilde{\tau} = \frac{2S}{n(n-1)} = \frac{(2)(27)}{(10)(10-1)} = .60 \quad (\text{Equation 30.2})$$

Equation 30.3 can also be employed to compute $\tilde{\tau}$.

$$\tilde{\tau} = 1 - \frac{4n_D}{n(n-1)} = 1 - \frac{(4)(9)}{10(10-1)} = .60 \quad (\text{Equation 30.3})$$

If there are no tied ranks present in the data, Equation 30.3 can be employed to compute **tau** in conjunction with a less tedious method than the one based on use of [Table 30.2](#). The alternative method (which becomes impractical when the sample size is large) involves the use of [Figure 30.1](#).

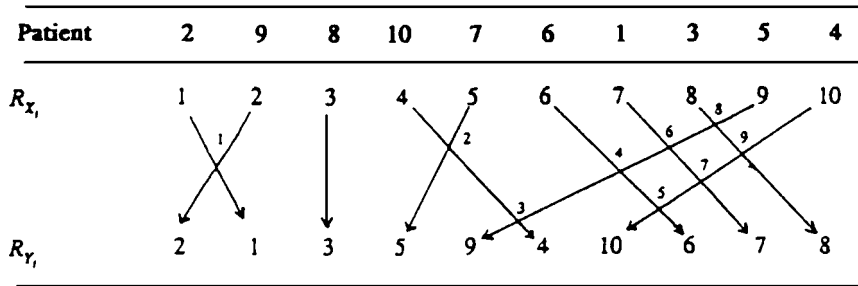


Figure 30.1 Visual Representation of Discordant Pairs of Ranks for Example 30.1

In [Figure 30.1](#) the values of R_{X_i} and R_{Y_i} are recorded as they appear in the second and third rows of [Table 30.2](#). Lines are drawn to connect each of the $n = 10$ corresponding values of R_{X_i} and R_{Y_i} . The total number of intersecting points in the diagram represents the number of discordant pairs of ranks or inversions in the data — i.e., the value of n_D . The value $n_D = 9$ along with the value $n = 10$ are substituted in Equation 30.3 to compute the value $\tilde{\tau} = .60$. Although not required for use in the latter equation, the number of concordant ranks (which, along with n_D , are employed in Equation 30.1) can be computed as follows: $n_C = [n(n-1)/2] - n_D$.

V. Interpretation of the Test Results

The obtained value $\tilde{\tau} = .60$ is evaluated with [Table A19](#) ([Table of Critical Values for Kendall's Tau](#)) in the [Appendix](#). Note that [Table A19](#) lists critical values for both **tau** and S .⁵ [Table 30.3](#) lists the tabled critical two-tailed and one-tailed .05 and .01 values for **tau** and S for $n = 10$.

Table 30.3 Exact Tabled Critical Values for $\tilde{\tau}$ and S for $n = 10$

	$\tilde{\tau}_{.05}/S_{.05}$	$\tilde{\tau}_{.01}/S_{.01}$
Two-tailed values	$\tilde{\tau} = .511$ $S = 23$	$\tilde{\tau} = .644$ $S = 29$
One-tailed values	$\tilde{\tau} = .467$ $S = 21$	$\tilde{\tau} = .600$ $S = 27$

The following guidelines are employed in evaluating the null hypothesis.

a) If the nondirectional alternative hypothesis $H_1: \tau \neq 0$ is employed, the null hypothesis can be rejected if the obtained absolute value of $\tilde{\tau}$ (or S) is equal to or greater than the tabled critical two-tailed value at the prespecified level of significance.

b) If the directional alternative hypothesis $H_1: \tau > 0$ is employed, the null hypothesis can be rejected if the sign of $\tilde{\tau}$ (or S) is positive, and the obtained value of $\tilde{\tau}$ (or S) is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

c) If the directional alternative hypothesis $H_1: \tau < 0$ is employed, the null hypothesis can be rejected if the sign of $\tilde{\tau}$ (or S) is negative, and the obtained absolute value of $\tilde{\tau}$ (or S) is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

Employing the above guidelines, the nondirectional alternative hypothesis $H_1: \tau \neq 0$ is supported at the .05 level, since the computed value $\tilde{\tau} = .60$ ($S = 27$) is greater than the tabled critical two-tailed value $\tilde{\tau}_{.05} = .511$ ($S_{.05} = 23$). It is not supported at the .01 level, since $\tilde{\tau} = .60$ ($S = 27$) is less than the tabled critical two-tailed value $\tilde{\tau}_{.01} = .644$ ($S_{.01} = 29$).

The directional alternative hypothesis $H_1: \tau > 0$ is supported at the .05 level, since the computed value $\tilde{\tau} = .60$ is a positive number that is greater than the tabled critical one-tailed value $\tilde{\tau}_{.05} = .467$ ($S_{.05} = 21$). It is also supported at the .01 level, since $\tilde{\tau} = .60$ is equal to the tabled critical one-tailed value $\tilde{\tau}_{.01} = .600$ ($S_{.01} = 27$).

The directional alternative hypothesis $H_1: \tau < 0$ is not supported, since the computed value $\tilde{\tau} = .60$ (S) is a positive number.

Test 30a: Test of significance for Kendall's tau When $n > 10$, the normal distribution provides an excellent approximation of the sampling distribution of **tau**. Equation 30.4 is the normal approximation for evaluating the null hypothesis $H_0: \tau = 0$.

$$z = \frac{3\tilde{\tau}\sqrt{n(n-1)}}{\sqrt{2(2n+5)}} \quad \text{(Equation 30.4)}$$

In view of the fact that the sample size $n = 10$ employed in Example 30.1 is just one subject below the minimum value generally recommended for use with Equation 30.4, the normal approximation will still provide a reasonably good approximation of the exact sampling distribution. When the appropriate values from Example 30.1 are substituted in Equation 30.4, the value $z = 2.41$ is computed.

$$z = \frac{(3)(.60)\sqrt{10(10-1)}}{\sqrt{2[(2)(10)+5]}} = 2.41$$

Equations 30.5 and 30.6 are alternative equations for computing the value of z that yield the identical result.⁶

$$z = \frac{\tilde{\tau}}{\sqrt{\frac{2(2n+5)}{9n(n-1)}}} = \frac{.60}{\sqrt{\frac{(2)[(2)(10)+5]}{(9)(10)(10-1)}}} = 2.41 \quad \text{(Equation 30.5)}$$

$$z = \frac{S}{\sqrt{\frac{n(n-1)(2n+5)}{18}}} = \frac{27}{\sqrt{\frac{(10)(10-1)[(2)(10)+5]}{18}}} = 2.41 \quad \text{(Equation 30.6)}$$

The computed value $z = 2.41$ is evaluated with **Table A1 (Table of the Normal Distribution)** in the **Appendix**. In the latter table, the tabled critical two-tailed .05 and .01 values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed .05 and .01 values are $z_{.05} = 1.65$ and $z_{.01} = 2.33$. Since the sign of the z value computed with Equations 30.4–30.6 will always be the same as the sign of $\tilde{\tau}$ (and S), the guidelines that are described earlier in this section for evaluating a $\tilde{\tau}$ (or S) value can also be applied in evaluating the z value computed with Equations 30.4–30.6 (i.e., substitute z in place of $\tilde{\tau}$ (or S) in the text of the guidelines for evaluating $\tilde{\tau}$ (or S)).

Employing the guidelines, the nondirectional alternative hypothesis $H_1: \tau \neq 0$ is supported at the .05 level, since the computed value $z = 2.41$ is greater than the tabled critical two-tailed value $z_{.05} = 1.96$. It is not, however, supported at the .01 level, since $z = 2.41$ is less than the tabled critical two-tailed value $z_{.01} = 2.58$.

The directional alternative hypothesis $H_1: \tau > 0$ is supported at both the .05 and .01 levels, since the computed value $z = 2.41$ is a positive number that is greater than the tabled critical one-tailed values $z_{.05} = 1.65$ and $z_{.01} = 2.33$.

The directional alternative hypothesis $H_1: \tau < 0$ is not supported, since the computed value $z = 2.41$ is a positive number. In order for the alternative hypothesis $H_1: \tau < 0$ to be supported, the computed value of z must be a negative number (as well as the fact that the absolute value of z must be equal to or greater than the tabled critical one-tailed value at the prespecified level of significance).

Note that the results for the normal approximation are identical to those obtained when the exact values of the sampling distribution of **tau** are employed. A summary of the analysis of Example 30.1 follows: It can be concluded that there is a significant monotonic increasing/positive relationship between the rankings of the two judges.⁷ The result of the analysis (based on the critical values in **Table 30.3** and the normal approximation) can be summarized as follows (if it is assumed the nondirectional alternative hypothesis $H_1: \tau \neq 0$ is employed): $\tilde{\tau} = .60$, $p < .05$.

It is noted in Section I that if both **Kendall's tau** and **Spearman's rho** are computed for the same set of data, the two measures will result in essentially the same conclusions with respect to whether the value of the underlying population correlation equals zero. In order to demonstrate this, employing the relevant values from **Table 30.1** in Equation 29.1, the value $r_s = .733$ is computed for Example 30.1.⁸

$$r_s = 1 - \frac{6\sum d^2}{n(n^2 - 1)} = 1 - \frac{6(44)}{10[(10)^2 - 1]} = .733$$

Note that the values $\tilde{\tau} = .60$ and $r_s = .733$ computed for Example 30.1 are not identical to one another, and that as noted in Section I, the absolute value of $\tilde{\tau}$ is less than the absolute value of r_s . It is also the case that the inequality $-1 \leq (3\tilde{\tau} - 2r_s) \leq 1$ (which is noted in Section I) is substantiated, since $(3)(.60) - (2)(.733) = .334$ (which falls within the range -1 to $+1$).

The computed value $r_s = .733$ is evaluated with **Table A18 (Table of Critical Values for Spearman's Rho)** in the **Appendix**. Employing the latter table, it is determined that for $n = 10$, the tabled critical two-tailed .05 and .01 values are $r_{s_{.05}} = .648$ and $r_{s_{.01}} = .794$, and the tabled critical one-tailed .05 and .01 values are $r_{s_{.05}} = .564$ and $r_{s_{.01}} = .745$. Employing the aforementioned critical values, the nondirectional alternative hypothesis $H_1: \rho_s \neq 0$ and the directional alternative hypothesis $H_1: \rho_s > 0$ are supported at the .05 level, since the computed value $r_s = .733$ is greater than the tabled critical two-tailed value $r_{s_{.05}} = .648$ and

the tabled critical one-tailed value $r_{s_{.05}} = .564$. The alternative hypotheses are not supported at the .01 level, since $r_s = .733$ is less than the tabled critical two-tailed value $r_{s_{.01}} = .794$ and the tabled critical one-tailed value $r_{s_{.01}} = .745$. This result is almost identical to that obtained when **Kendall's tau** is employed (although in the analysis for **Kendall's tau**, the directional alternative hypothesis $H_1: \tau > 0$ is supported at the .01 level).

If the computed value $r_s = .733$ is evaluated with Equation 29.2, the value $t = 3.05$ is computed.

$$t = \frac{r_s \sqrt{n-2}}{\sqrt{1-r_s^2}} = \frac{.733 \sqrt{10-2}}{\sqrt{1-(.733)^2}} = 3.05$$

The t value computed with Equation 29.2 is evaluated with **Table A2 (Table of Student's t Distribution)** in the **Appendix**. The degrees of freedom employed are $df = n - 2$. Employing **Table A2**, it is determined that for $df = 10 - 2 = 8$, the tabled critical two-tailed .05 and .01 values are $t_{.05} = 2.31$ and $t_{.01} = 3.36$, and the tabled critical one-tailed .05 and .01 values are $t_{.05} = 1.86$ and $t_{.01} = 2.90$. Employing the aforementioned critical values, the nondirectional alternative hypothesis $H_1: \rho_s \neq 0$ is supported at the .05 level, since the computed value $t = 3.05$ is greater than the tabled critical two-tailed value $t_{.05} = 2.31$. It is not supported at the .01 level, since $t = 3.05$ is less than $t_{.01} = 3.36$. The directional alternative hypothesis $H_1: \rho_s > 0$ is supported at both the .05 and .01 levels, since the computed value $t = 3.05$ is a positive number (since $r_s = .733$ is a positive number) that is greater than the tabled critical one-tailed values $t_{.05} = 1.86$ and $t_{.01} = 2.90$. This result is identical to that obtained when **Kendall's tau** is employed.

The slight discrepancies between the various methods for assessing the significance of $\tilde{\tau}$ and r_s can be attributed to the fact that the values in **Table A18** and the result of Equation 29.2 are approximations of the exact sampling distribution of **Spearman's rho**, as well as the fact that the use of the normal distribution for assessing the significance of **tau** also represents an approximation of an exact sampling distribution. However, for the most part, regardless of whether one elects to compute $\tilde{\tau}$ or r_s as the measure of association for Example 30.1, it will be concluded that the population correlation is some value other than zero, and the latter conclusion will be reached irrespective of whether a nondirectional or directional alternative hypothesis is employed.

VI. Additional Analytical Procedures for Kendall's Tau and/or Related Tests

1. Tie correction for Kendall's tau When one or more ties are present in a set of data, it is necessary to employ a tie correction in order to compute the value of $\tilde{\tau}$. To illustrate how ties are handled, let us assume that **Table 30.4** summarizes the data for Example 30.1. Note that in contrast to **Table 30.2**, the data in **Table 30.4** are characterized by the presence of ties on both the X and Y variables. Specifically, Subjects 2 and 9 are tied for the first ordinal position on the X variable, Subjects 8 and 10 are tied for the third ordinal position on the Y variable, and Subjects 6 and 7 are tied for the ninth ordinal position on the Y variable.

As is the case for **Table 30.2**, the entries **C** and **D** are employed in the cells of **Table 30.4** to indicate concordant versus discordant pairs of ranks. There are, however, three cells in **Table 30.4** that involve tied ranks in which the cell entry is **0**. Note that if the R_{Y_i} value for a row is equal to a R_{Y_j} that falls in a column to its right, a **0** is written in the cell that is the intersection of

that row and column. Since, however, this protocol only takes into account ties on the Y variable, it will not allow one to identify all of the cells in the table for which **0** is the appropriate entry. In point of fact, a **0** entry should also appear in any cell that involves a pair of tied observations on the X variable, even though the two ranks on the Y variable with which the X variable pair is being contrasted are not tied. In the above example there is just one set of ties on the X variable (the rank of 1.5 for Subjects 2 and 9). Note that the cell identified with an asterisk in the upper left of the table has a **0** entry, even though the rank-order directly to the right of the value $R_{Y_2} = 2$ (which is the rank of Subject 2 on the Y variable) is $R_{Y_9} = 1$ (which is the rank of Subject 9 on the Y variable). If the protocol described for Table 30.2 is employed, since the rank-order $R_{Y_9} = 1$ to the right of $R_{Y_2} = 2$ is less than the latter value, a **D** should be placed in that cell. The reason for employing a **0** in the cell is that if the arrangement of the ranks on the X variable is reversed, with Subject 9 listed first and Subject 2 listed second, the value of R_{Y_i} for that row will be $R_{Y_9} = 1$, and the first rank/ R_{Y_j} value that it will be compared with will be $R_{Y_2} = 2$. If the latter arrangement is employed in conjunction with the protocol described for Table 30.2, the appropriate entry for the cell under discussion is a **C**. Thus, whenever a different arrangement of the tied ranks on the X variable will result in a different letter entry for a cell (i.e., **C** versus **D**), that cell is assigned a **0**.

Table 30.4 Computational Table for Kendall's Tau Involving Ties

Subject	2	9	8	10	7	6	1	3	5	4	ΣC	ΣD
R_{X_i}	1.5	1.5	3	4	5	6	7	8	9	10		
R_{Y_i}	2	1	3.5	3.5	9.5	9.5	5	6	7	8		
	2	0*	C	C	C	C	C	C	C	C	8	0
		1	C	C	C	C	C	C	C	C	8	0
			3.5	0	C	C	C	C	C	C	6	0
				3.5	C	C	C	C	C	C	6	0
					9.5	0	D	D	D	D	0	4
						9.5	D	D	D	D	0	4
							5	C	C	C	3	0
								6	C	C	2	0
									7	C	1	0
										8	0	0
$\Sigma \Sigma C = n_C = 34 \quad \Sigma \Sigma D = n_D = 8$												

A general protocol for determining whether a cell should be assigned a **0** to represent a tie can be summarized as follows: a) If the R_{Y_i} value at the left of a row is tied with an R_{Y_j} value that falls in a column to its right, a **0** should be placed in the cell that is the intersection of that row and column; and b) If there is a tie between the values of R_{X_i} and R_{X_j} that fall directly above the values of R_{Y_i} and R_{Y_j} being compared, a **0** should be placed in the cell that is the intersection of the row and column the values R_{Y_i} and R_{Y_j} (as well as R_{X_j}) appear.

It should be noted that when there are no ties present in the data, $n_C + n_D = [n(n - 1)]/2$. Thus, in the case of Table 30.2, $(n_C = 36) + (n_D = 9) = [(10)(10 - 1)]/2 = 45$. When, on the other hand, ties are present in the data, since entries of **0** are not counted as either concordant or discordant pairs, $n_C + n_D \neq [n(n - 1)]/2$. The latter can be confirmed by the fact that in Table 30.4, $(n_C = 34) + (n_D = 8) \neq [(10)(10 - 1)]/2$.

The computation of the value of **Kendall's tau** using the tie correction will now be described. In the example under discussion there is $s = 1$ set of ties involving the ranks of subjects' X scores (Subjects 2 and 9), and $s = 2$ sets of ties involving the ranks of subjects' Y scores (Subjects 8 and 10; Subjects 6 and 7). Equation 30.9 is employed to compute the tie-corrected value of **Kendall's tau**, which will be represented by the notation $\tilde{\tau}_c$. Note that the values $\sum T_X$ and $\sum T_Y$ in Equation 30.9 are computed with Equations 30.7 and 30.8. In Equation 30.7, $t_{i(x)}$ represents the number of X scores that are tied for a given rank. In Equation 30.8, $t_{i(y)}$ represents the number of Y scores that are tied for a given rank. The notations $\sum_{i=1}^s (t_{i(x)}^2 - t_{i(x)})$ and $\sum_{i=1}^s (t_{i(y)}^2 - t_{i(y)})$ indicate that the following is done with respect to each of the variables: a) For each set of ties, the number of ties in the set is subtracted from the square of the number of ties in that set; and b) The sum of all the values computed in part a) is obtained for that variable.

When the data from Table 30.4 are substituted in Equations 30.7–30.9, the tie-corrected value $\tilde{\tau}_c = .598$ is computed.⁹

$$T_X = \sum_{i=1}^s (t_{i(x)}^2 - t_{i(x)}) = [(2)^2 - 2] = 2 \quad (\text{Equation 30.7})$$

$$T_Y = \sum_{i=1}^s (t_{i(y)}^2 - t_{i(y)}) = [(2)^2 - 2] + [(2)^2 - 2] = 4 \quad (\text{Equation 30.8})$$

$$\begin{aligned} \tilde{\tau}_c &= \frac{2(n_C - n_D)}{\sqrt{n(n-1) - T_X} \sqrt{n(n-1) - T_Y}} \\ &= \frac{(2)(34 - 8)}{\sqrt{10(10-1) - 2} \sqrt{10(10-1) - 4}} = .598 \end{aligned} \quad (\text{Equation 30.9})$$

2. Regression analysis and Kendall's tau As noted in the discussion of **Spearman's rank-order correlation coefficient**, regression analysis procedures have been developed for rank-order data. Sources for nonparametric regression analysis (including monotonic regression analysis) are cited in Section VI of the latter test.

3. Partial rank correlation The computation of a **partial correlation coefficient** (described in Section IX of the **Pearson product-moment correlation coefficient**, and discussed briefly in Section VI of **Spearman's rank-order correlation coefficient**), can be extended to **Kendall's tau**. Thus, when the rank-orders for three variables are evaluated, Equation 28.72 can be employed to compute one or more **partial correlation coefficients** for **Kendall's tau** (employing the relevant values of $\tilde{\tau}$ in the equation). Conover (1980, 1999), Daniel (1990), Marascuilo and McSweeney (1977), and Siegel and Castellan (1988) discuss the computation of a **partial correlation coefficient** in reference to **Kendall's tau**. It should be noted that the partial rank-order correlation coefficient for **Kendall's tau** employs a different sampling distribution than the one that is employed for evaluating $\tilde{\tau}$. Tables for the appropriate sampling distribution can be found in Daniel (1990) and Siegel and Castellan (1988).

4. Sources for computing a confidence interval for Kendall's tau A procedure (attributed to Noether (1967)) for deriving a confidence interval for **Kendall's tau** is described in Daniel (1990).

VII. Additional Discussion of Kendall's Tau

1. Power efficiency of Kendall's tau Daniel (1990) and Siegel and Castellan (1988) note that (for large sample sizes) the **asymptotic relative efficiency** (which is discussed in Section VII of the **Wilcoxon signed-ranks test (Test 6)** of **Kendall's tau** relative to the **Pearson product-moment correlation coefficient** is approximately .91 (when the assumptions underlying the latter test are met).

2. Kendall's coefficient of agreement **Kendall's coefficient of agreement** is another measure of association that allows a researcher to evaluate the degree of agreement between m sets of ranks on n subjects/objects. The latter measure, which is described in Siegel and Castellan (1988), is essentially an extension of **Kendall's tau** to more than two sets of ranks. The relationship between **Kendall's tau** and **Kendall's coefficient of agreement** is analogous to the relationship between **Spearman's rho** and **Kendall's coefficient of concordance (Test 31)**.

VIII. Additional Examples Illustrating the Use of Kendall's Tau

Since **Spearman's rho** and **Kendall's tau** can be employed to evaluate the same data, Examples 29.1 and 29.2, as well as the data set presented in [Tables 29.2/29.4](#), can be evaluated with **Kendall's tau**. It is also the case, that if a researcher elects to rank-order the scores of subjects in any of the examples for which the **Pearson product-moment correlation coefficient** is employed, a value can be computed for **Kendall's tau**. To illustrate this, Example 28.1 (which is identical to Example 29.1) will be evaluated with **Kendall's tau**. The rank-orders of the scores of subjects on the X and Y variables in Examples 28.1/29.1 are arranged in [Figure 30.2](#). The arrangement of the ranks in [Figure 30.2](#) allows for use of the protocol for determining the number of discordant pairs of ranks that is described in reference to [Figure 30.1](#). Since none of the vertical lines intersect, the number of pairs of discordant ranks is $n_D = 0$. Since each subject has the identical rank on both the X and the Y variables, all of the pairs of ranks are concordant. The total number of pairs of ranks is $[(5)(5 - 1)]/2 = 10$, which is also the value of n_C .

Subject	2	3	5	4	1
R_{X_i}	1	2	3	4	5
	↓	↓	↓	↓	↓
R_{Y_i}	1	2	3	4	5

Figure 30.2 Visual Representation of Discordant Pairs of Ranks for Examples 28.1/29.1

Employing the values $n = 5$ and $n_D = 0$ in Equation 30.3, the value $\tilde{\tau} = 1$ is computed. The same value can also be computed with either Equation 30.1 or Equation 30.2, if the values $n_C = 10$ and/or $S = 10$ are employed in the aforementioned equations.

$$\tilde{\tau} = 1 - \frac{(4)(0)}{5(5 - 1)} = 1$$

$\tilde{\tau} = 1$ is identical to the value $r_s = 1$ computed for the same set of data. As noted in Section I, when there is a perfect positive or negative correlation between the variables, identical values are computed for $\tilde{\tau}$ and r_s .

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Endnotes

1. A discussion of monotonic relationships can be found in Section I of **Spearman's rank-order correlation coefficient**.
2. The exception to this is that when the computed value of $\bar{\tau}$ is either +1 or -1, the identical value will be computed for r_s .
3. The **coefficient of determination** is discussed in Section V of the **Pearson product-moment correlation coefficient**.
4. a) Some sources employ the following statements as the null hypothesis and the non-directional alternative hypothesis for **Kendall's tau**: **Null hypothesis**: H_0 : Variables X and Y are independent of one another; **Nondirectional alternative hypothesis**: H_1 : Variables X and Y are not independent of one another.

It is, in fact, true that if in the underlying population the two variables are independent, the value of τ will equal zero. However, the fact that $\tau = 0$, in and of itself, does not ensure that the variables are independent of one another. Thus, it is conceivable that in a population in which the correlation between X and Y is $\tau = 0$, a nonmonotonic curvilinear function can be employed to describe the relationship between the variables.

b) Note that in Example 30.1 the scores of subjects (who are the patients) on the X and

Y variables are the respective ranks assigned to the subjects/patients by Dr. X and Dr. Y. Thus, the null hypothesis can also be stated as follows: In the underlying population the sample of subjects/patients represents, the correlation between the rankings of Dr. X and Dr. Y equals 0.

5. If either of the two values $\tilde{\tau}$ or S is known, Equation 30.2 can be employed to compute the other value. Some sources only list critical values for one of the two values $\tilde{\tau}$ or S .
6. The following should be noted with respect to Equations 30.5 and 30.6: a) The denominator of Equation 30.5 is the standard deviation of the sampling distribution of the normal approximation of **tau**; and b) Based on a recommendation by Kendall (1970), Marascuilo and McSweeney (1977) (who employ Equation 30.6) describe the use of a correction for continuity for the normal approximation. In employing the correction for continuity with Equation 30.6, when S is a positive number, the value 1 is subtracted from S , and when S is a negative number, the value 1 is added to S . The correction for continuity (which is not employed by most sources) reduces the absolute value of z , thus resulting in a more conservative test. The rationale for employing a correction for continuity for a normal approximation of a sampling distribution is discussed in Section VI of the **Wilcoxon signed-ranks test**.
7. Howell (1992, 1997) notes that the value $\tilde{\tau} = .60$ indicates that if a pair of subjects are randomly selected, the likelihood that the pair will be ranked in the same order is .60 higher than the likelihood that they will be ranked in the reverse order.
8. The data for Examples 30.1 and 29.2 are identical, except for the fact that in the latter example there is a tie for the X score in the second ordinal position which involves the X scores in the eighth and ninth rows.
9. If Equation 30.1 is employed to compute the value of $\tilde{\tau}$ for the data in [Table 30.4](#), the value $\tilde{\tau} = .578$ is computed. As noted in the text, because of the presence of ties, $n_C + n_D \neq [n(n - 1)]/2$.

$$\tilde{\tau} = \frac{34 - 8}{\left[\frac{10(10 - 1)}{2} \right]} = .578$$

Test 31

Kendall's Coefficient of Concordance (Nonparametric Measure of Association/Correlation Employed with Ordinal Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Kendall's coefficient of concordance is one of a number of measures of correlation or association discussed in this book. Measures of correlation are not inferential statistical tests, but are, instead, descriptive statistical measures that represent the degree of relationship between two or more variables. Upon computing a measure of correlation, it is common practice to employ one or more inferential statistical tests in order to evaluate one or more hypotheses concerning the correlation coefficient. The hypothesis stated below is the most commonly evaluated hypothesis for **Kendall's coefficient of concordance**.

Hypothesis evaluated with test In the underlying population represented by a sample, is the correlation between m sets of ranks some value other than zero? The latter hypothesis can also be stated in the following form: In the underlying population represented by the sample, are m sets of ranks independent of one another?

Relevant background information on test Developed independently by Kendall and Babington-Smith (1939) and Wallis (1939), **Kendall's coefficient of concordance** is a measure of correlation/association that is employed for three or more sets of ranks. Specifically, **Kendall's coefficient of concordance** is a measure that allows a researcher to evaluate the degree of agreement between m sets of ranks for n subjects/objects. The population parameter estimated by the correlation coefficient will be represented by the notation W . The sample statistic computed to estimate the value of W will be represented by the notation \tilde{W} . The range of possible values within which **Kendall's coefficient of concordance** may fall is $0 \leq \tilde{W} \leq +1$.¹ When there is complete agreement among all m sets of ranks, the value of \tilde{W} will equal 1.¹ When, on the other hand, there is no pattern of agreement among the m sets of ranks, \tilde{W} will equal 0. The value of \tilde{W} cannot be a negative number, since when there are more than two sets of ranks it is not possible to have complete disagreement among all the sets. Because of this, it becomes meaningless to use a negative correlation to describe the degree of association in the data when $m \geq 3$.

It is important to note that **Kendall's coefficient of concordance** is related to both **Spearman's rank-order correlation coefficient (Test 29)** and **Friedman's two-way analysis of variance by ranks (Test 25)**. Specifically: a) The computed value of \tilde{W} for m sets of ranks is linearly related to the average value of **Spearman's rho** that can be computed for all possible pairs of ranks. The relationship between **Kendall's coefficient of concordance** and **Spearman's rank-order correlation coefficient** is discussed in greater detail in Section VII. It should be noted that although **Kendall's coefficient of concordance** can be computed for two sets of ranks, in practice it is not. The latter can be attributed to the fact that in contrast to **Spearman's rho** and

Kendall's tau (which are the measures of association that are employed with two sets of ranks), the value of \tilde{W} cannot be a negative number (which in the case of **Spearman's rho** and **Kendall's tau** indicates the presence of an inverse relationship). Because the measures of association that are employed with two sets of ranks can assume a negative value, \tilde{W} is not directly comparable to them;² and b) Although they were developed independently, **Kendall's coefficient of concordance** and **Friedman's two-way analysis of variance by ranks** are based on the same mathematical model. Because of this, for a given set of data, the values computed for χ_r^2 (which is the **Friedman test** statistic) and \tilde{W} can be algebraically derived from one another. The relationship between **Kendall's coefficient of concordance** and **Friedman's two-way analysis of variance by ranks** is discussed in Section VII.

II. Example

Example 31.1 *Six instructors at an art institute rank four students with respect to artistic ability. A rank of 1 is assigned to the student with the highest level of ability and a rank of 4 to the student with the lowest level of ability. The rankings of the six instructors for the four students are summarized in Table 31.1. Is there a significant association between the rank-orders assigned to the four students by the six instructors?*

Table 31.1 Data for Example 31.1

Instructor	Student				Totals
	1	2	3	4	
1	3	2	1	4	
2	3	2	1	4	
3	3	2	1	4	
4	4	2	1	3	
5	3	2	1	4	
6	4	1	2	3	
ΣR_j	20	11	7	22	$T = 60$
$(\Sigma R_j)^2$	400	121	49	484	$U = 1054$

III. Null versus Alternative Hypotheses

Upon computing **Kendall's coefficient of concordance**, it is common practice to determine whether the obtained value of the correlation coefficient is large enough to allow a researcher to conclude that the underlying population correlation coefficient between the m sets of ranks is some value other than zero. Section V describes how the latter hypothesis, which is stated below, can be evaluated through use of tables of critical \tilde{W} values or through use of an inferential statistical test that is based on the chi-square distribution.

Null hypothesis $H_0: W = 0$

(In the underlying population the sample represents, the correlation between the $m = 6$ sets of ranks equals 0.)

Alternative hypothesis $H_1: W \neq 0$

(In the underlying population the sample represents, the correlation between the $m = 6$ sets of ranks equals some value other than 0. This is equivalent to stating that the $m = 6$ sets of ranks are

not independent of one another. When there are more than two sets of ranks, the alternative hypothesis will always be stated **nondirectionally**.³ In order to be significant, the obtained value of \tilde{W} must be equal to or greater than the tabled critical value of \tilde{W} at the prespecified level of significance.)

IV. Test Computations

The data for Example 31.1 are summarized in Table 31.1. Note that in Table 31.1 there are $m = 6$ instructors, who are represented by the six rows, and $n = 4$ students who are represented by the four columns.

The summary values $T = 60$ and $U = 1054$ in Table 31.1 are computed as follows.

$$T = \sum_{j=1}^n (\Sigma R_j) = \Sigma R_1 + \Sigma R_2 + \Sigma R_3 + \Sigma R_4 = 20 + 11 + 7 + 22 = 60$$

$$\begin{aligned} U &= \sum_{j=1}^n (\Sigma R_j)^2 = (\Sigma R_1)^2 + (\Sigma R_2)^2 + (\Sigma R_3)^2 + (\Sigma R_4)^2 \\ &= (20)^2 + (11)^2 + (7)^2 + (22)^2 = 400 + 121 + 49 + 484 = 1054 \end{aligned}$$

The **coefficient of concordance** is a ratio of the variance of the sums of the ranks for the subjects (i.e., the variance of the ΣR_j values) divided by the maximum possible value that can be computed for the variance of the sums of the ranks (for the relevant values of m and n). Equation 31.1 summarizes the definition of \tilde{W} .

$$\tilde{W} = \frac{\text{Variance of } \Sigma R_j \text{ values}}{\text{Maximum possible variance for } \Sigma R_j \text{ values for relevant values of } m \text{ and } n} \quad (\text{Equation 31.1})$$

The variance of the ΣR_j values (which is represented by the notation S) is computed with Equation 31.2.

$$S = \frac{nU - (T)^2}{n} \quad (\text{Equation 31.2})$$

Substituting the appropriate values from Example 31.1 in Equation 31.2, the value $S = 154$ is computed.

$$S = \frac{(4)(1054) - (60)^2}{4} = 154$$

\tilde{W} is computed with Equation 31.3. The denominator of Equation 31.3 (which for Example 31.1 equals 180) represents the maximum possible value that can be computed for the variance of the sums of the ranks. The only time the value of S will equal the value of the denominator of Equation 31.3 (thus resulting in the value $\tilde{W} = 1$) will be when there is perfect agreement among the m judges with respect to their rankings of the n subjects.

$$\tilde{W} = \frac{S}{\left(\frac{m^2 n (n^2 - 1)}{12} \right)} \quad (\text{Equation 31.3})$$

Substituting the appropriate values in Equation 31.3, the value $\tilde{W} = .856$ is computed.

$$\tilde{W} = \frac{154}{\left(\frac{(6)^2(4)[(4)^2 - 1]}{12} \right)} = .856$$

Equation 31.4 is an alternative computationally quicker equation for computing the value of \tilde{W} . Equation 31.4, however, does not allow for the direct computation of S . The latter fact is noted, since some of the tables employed to evaluate whether \tilde{W} is significant list critical values for S rather than critical values for \tilde{W} .

(Equation 31.4)

$$\tilde{W} = \frac{12U - 3m^2n(n+1)^2}{m^2n(n^2 - 1)} = \frac{(12)(1054) - (3)(6)^2(4)(4+1)^2}{(6)^2(4)[(4)^2 - 1]} = .856$$

The fact the value of \tilde{W} is close to 1 indicates that there is a high degree of agreement among the six instructors with respect to how they rank the four students.

V. Interpretation of the Test Results

The obtained value $\tilde{W} = .856$ is evaluated with **Table A20 (Table of Critical Values for Kendall's Coefficient of Concordance)** in the **Appendix**. Note that **Table A20** lists critical values for both \tilde{W} and S . The S values in **Table A20** are extracted from Friedman (1940), and the values of \tilde{W} were computed by substituting the appropriate value of S in Equation 31.3. In order to reject the null hypothesis, the computed value of \tilde{W} (or S) must be equal to or greater than the tabled critical value at the prespecified level of significance. For $m = 6$ and $n = 4$, the tabled critical .05 and .01 values for \tilde{W} (S) in **Table A20** are $\tilde{W}_{.05} = .421$ ($S_{.05} = 75.7$) and $\tilde{W}_{.01} = .553$ ($S_{.01} = 99.5$). Since the computed value $\tilde{W} = .856$ ($S = 154$) is greater than all of the aforementioned critical values, the alternative hypothesis $H_1: W \neq 0$ is supported at both the .05 and .01 levels.

Test 31a: Test of significance for Kendall's coefficient of concordance When exact tables for \tilde{W} (or S) are not available, the chi-square distribution provides a reasonably good approximation of the sampling distribution of \tilde{W} . The chi-square approximation of the sampling distribution of \tilde{W} is computed with Equation 31.5. The degrees of freedom employed for Equation 31.5 are $df = n - 1$.

$$\chi^2 = m(n - 1)\tilde{W} \quad \text{(Equation 31.5)}$$

When the appropriate values from Example 31.1 are substituted in Equation 31.5, the value $\chi^2 = 15.41$ is computed.

$$\chi^2 = (6)(4 - 1)(.856) = 15.41$$

The value $\chi^2 = 15.41$ is evaluated with **Table A4 (Table of the Chi-Square Distribution)** in the **Appendix**. In order to reject the null hypothesis, the obtained value of χ^2 must be equal to or greater than the tabled critical value at the prespecified level of significance. For $df = 4 - 1 = 3$, the tabled critical values are $\chi^2_{.05} = 7.81$ and $\chi^2_{.01} = 11.34$ (which are the chi-square values at the 95th and 99th percentiles). Since $\chi^2 = 15.41$ is greater than both of the

aforementioned critical values, the alternative hypothesis $H_1: W \neq 0$ is supported at both the .05 and .01 levels.

For small sample sizes, the exact sampling distribution of the **Friedman two-way analysis of variance by ranks** (which, as noted in Section I, is mathematically equivalent to **Kendall's coefficient of concordance**) can be employed to evaluate the significance of \tilde{W} . In addition, when the values of m and n are reasonably small, some sources (e.g., Marascuilo and McSweeney (1977) and Siegel and Castellan (1988)) evaluate the significance of \tilde{W} by employing an adjusted chi-square value (discussed in Section VII of the **Friedman two-way analysis of variance by ranks**) which represents an exact value for the underlying sampling distribution. For $m = 6$ and $n = 4$, the adjusted/exact .05 and .01 critical values are $\chi^2_{r_{.05}} = 7.60$ and $\chi^2_{r_{.01}} = 10.00$ (which are reasonably close to the values $\chi^2_{.05} = 7.81$ and $\chi^2_{.01} = 11.34$). Since the computed value $\chi^2 = 15.41$ is greater than both of the aforementioned critical values, the alternative hypothesis $H_1: W \neq 0$ is supported at both the .05 and .01 levels. Thus, regardless of which tables are employed to evaluate the results of Example 31.1, the alternative hypothesis $H_1: W \neq 0$ is supported at both the .05 and .01 levels. Consequently, one can conclude there is a significant association among the six instructors with respect to how they rank the four students.

VI. Additional Analytical Procedures for Kendall's Coefficient of Concordance and/or Related Tests

1. Tie correction for Kendall's coefficient of concordance When ties are present in a set of data, some sources recommend that the value of \tilde{W} computed with Equations 31.3/31.4 be adjusted. Unless there is an excessive number of ties, the difference between the value of \tilde{W} computed with Equations 31.3/31.4 and the value computed with the tie correction will be minimal. The tie correction, which results in a slight increase in the value of \tilde{W} , will be illustrated with Example 31.2.

Example 31.2 *Four judges rank four contestants in a beauty contest. The judges are told to assign the most beautiful contestant a rank of 1 and the least beautiful contestant a rank of 4. The rank-orders of the four judges are summarized in Table 31.2. Is there a significant association between the rank-orders assigned to the four contestants by the four judges?*

Table 31.2 Data for Example 31.2

Judge	Contestant				Totals
	1	2	3	4	
1	1	3	3	3	
2	1	4	2	3	
3	2	3	1	4	
4	1.5	1.5	3.5	3.5	
ΣR_j	5.5	11.5	9.5	13.5	$T = 40$
$(\Sigma R_j)^2$	30.25	132.25	90.25	182.25	$U = 435$

In Example 31.2, there are $m = 4$ sets of ranks/judges and $n = 4$ subjects/contestants who are ranked. Inspection of Table 31.2 reveals that Judges 1 and 4 employ tied ranks. As is the case with other rank-order tests described in the book, subjects who are tied for a specific rank are assigned the average of the ranks that are involved. Judge 1 assigns a rank of 1 to Contestant 1, and places the other three contestants in a tie for the next ordinal position. Thus, Contestants 2, 3, and 4 are all assigned a rank of 3, which is the average of the three ranks involved (i.e.,

$(2 + 3 + 4)/3 = 3$). Judge 4 places Contestants 1 and 2 in a tie for the first and second ordinal positions, and Contestants 3 and 4 in a tie for the third and fourth ordinal positions. Thus, the contestants evaluated by Judge 4 are assigned ranks that are the average of those ranks for which they are tied (i.e., $(1 + 2)/2 = 1.5$ and $(3 + 4)/2 = 3.5$).

Equation 31.6 (which is the tie-corrected version of Equation 31.4) is employed to compute the tie-corrected value of **Kendall's coefficient of concordance**, which will be represented by the notation \tilde{W}_c .

$$\tilde{W}_c = \frac{12U - 3m^2n(n + 1)^2}{m^2n(n^2 - 1) - m \sum_{i=1}^m \left[\sum_{a=1}^s (t_a^3 - t_a) \right]} \quad (\text{Equation 31.6})$$

The notation $\sum_{i=1}^m [\sum_{a=1}^s (t_a^3 - t_a)]$ in Equation 31.6 indicates the following: a) Within each set of ranks, for each set of ties that is present the number of ties in the set is subtracted from the cube of the number of ties in that set; b) The sum of all the values computed in part a) is obtained for that set of ranks; and c) The sum of the values computed in part b) is computed for the m sets of ranks.

In the case of Example 31.2, Judge 1 has $s = 1$ set of ties involving three contestants. Thus, for Judge 1, $\sum_{a=1}^s (t_a^3 - t_a) = [(3)^3 - 3] = 24$. Since Judges 2 and 3 do not employ any ties, the latter two judges will not contribute to the tie correction, and thus the value of $\sum_{a=1}^s (t_a^3 - t_a)$ will equal 0 for both of the aforementioned judges. Judge 4 has $s = 2$ sets of ties, each set involving two contestants. Thus, for Judge 4, $\sum_{a=1}^s (t_a^3 - t_a) = [(2)^3 - 2] + [(2)^3 - 2] = 12$. We can now determine the value $\sum_{i=1}^m [\sum_{a=1}^s (t_a^3 - t_a)] = 36$, which is employed in Equation 31.6.

$$\sum_{i=1}^m \left[\sum_{a=1}^s (t_a^3 - t_a) \right] = 24 + 0 + 0 + 12 = 36$$

When the appropriate values are substituted in Equation 31.6, the tie-corrected value $\tilde{W}_c = .51$ is computed for Example 31.2.⁴

$$\tilde{W}_c = \frac{(12)(435) - (3)(4)^2(4)(4 + 1)^2}{(4)^2(4)[(4)^2 - 1] - (4)(36)} = .51$$

It can be seen below that when Equation 31.4 (which does not employ the tie correction) is employed to compute \tilde{W} , the value $\tilde{W} = .44$ is obtained. Note that the latter value is less than $\tilde{W}_c = .51$. The computed correlation $\tilde{W}_c = .51$ (as well as $\tilde{W} = .44$) indicates a moderate degree of association between the four sets of ranks.

$$\tilde{W} = \frac{(12)(435) - (3)(4)^2(4)(4 + 1)^2}{(4)^2(4)[(4)^2 - 1]} = .44$$

Note that in **Table A20** the tabled critical .05 and .01 values for $m = 4$ and $n = 4$ are $\tilde{W}_{.05} = .619$ and $\tilde{W}_{.01} = .768$. Since both $\tilde{W}_c = .51$ and $\tilde{W} = .44$ are less than $\tilde{W}_{.05} = .619$, the null hypothesis $H_0: W = 0$ cannot be rejected.

VII. Additional Discussion of Kendall's Coefficient of Concordance

1. Relationship between Kendall's coefficient of concordance and Spearman's rank-order correlation coefficient The relationship between **Kendall's coefficient of concordance** and **Spearman's rank-order correlation coefficient** is as follows: If for data consisting of m sets of ranks a value for **Spearman's rho** is computed for every possible pair consisting of two sets of ranks (i.e., if $m = 3$, $r_{S_{12}}$, $r_{S_{13}}$, $r_{S_{23}}$), the average of all the r_S values (to be designated \bar{r}_S) is a linear function of the value of \tilde{W} computed for the data. Equation 31.7 defines the exact relationship between **Spearman's rho** and \tilde{W} for the same set of data.

$$\bar{r}_S = \frac{m\tilde{W} - 1}{m - 1} \quad (\text{Equation 31.7})$$

The above relationship will be demonstrated employing the data in Table 31.3 (which we will assume is a revised set of data for Example 31.1, in which $m = 3$ and $n = 3$).

Table 31.3 Data for Use in Equation 31.7

Instructor	Student			Totals
	1	2	3	
1	3	1	2	
2	1	2	3	
3	3	2	1	
ΣR_j	7	5	6	$T = 18$
$(\Sigma R_j)^2$	49	25	36	$U = 110$

Substituting the appropriate values in Equation 31.4, the value $\tilde{W} = .111$ is computed. The latter value indicates a weak degree of association between the three sets of ranks.⁵

$$\tilde{W} = \frac{(12)(110) - (3)(3)^2(3)(3 + 1)^2}{(3)^2(3)[(3)^2 - 1]} = .111$$

Substituting $\tilde{W} = .111$ in Equation 31.7, the value $\bar{r}_S = -.333$ is computed.

$$\bar{r}_S = \frac{(3)(.111) - 1}{3 - 1} = -.333$$

We will now confirm that $\bar{r}_S = -.333$. Equation 29.1 is employed to compute the r_S values for the 3 pairs of ranks (i.e., $r_{S_{12}}$ for the ranks of Instructor 1 versus Instructor 2; $r_{S_{13}}$ for the ranks of Instructor 1 versus Instructor 3; $r_{S_{23}}$ for the ranks of Instructor 2 versus Instructor 3). The resulting values are $r_{S_{12}} = -.5$, $r_{S_{13}} = .5$, and $r_{S_{23}} = -1$. The average of the values of the three pairs of ranks is $\bar{r}_S = [(-.5) + .5 + (-1)]/3 = -.333$, thus confirming the result obtained with Equation 31.7. It should be noted that when Equation 31.7 is employed to compute the value of \bar{r}_S , the range of values within which \bar{r}_S can fall is defined by the following limits: $[-1/(m - 1)] \leq \bar{r}_S \leq +1$. When $m = 3$, as is the case in the example under discussion, the minimum possible value \bar{r}_S can assume is $-1/(3 - 1) = -.5$. Note that even though the sign of \tilde{W} cannot be negative, Equation 31.7 can convert a positive \tilde{W} value into either a positive or negative \bar{r}_S value.

The relationship described by Equation 31.7 can also be demonstrated for any of the examples employed in illustrating **Spearman's rank-order correlation coefficient**, where $m = 2$. To illustrate, in the case of Example 29.2 the value $r_s = .72$ is computed for two sets of ranks. When the relevant values from Example 29.2 (which are summarized in Table 29.6)⁶ are substituted in Equation 31.4, the value $\tilde{W} = .86$ is computed. Note that in Example 29.2, $m = 2$ and $n = 10$.

$$\tilde{W} = \frac{(12)(1493.5) - (3)(2)^2(10)(10 + 1)^2}{(2)^2(10)[(10)^2 - 1]} = .86$$

Substituting $\tilde{W} = .86$ in Equation 31.7 yields the value $\bar{r}_s = .72$, which equals $r_s = .72$ computed with Equation 29.1.

$$\bar{r}_s = \frac{(2)(.86) - 1}{2 - 1} = .72$$

Thus, when $m = 2$, the value of \bar{r}_s will equal r_s , since the average of a single value (based on one pair of ranks) is that value.

2. Relationship between Kendall's coefficient of concordance and the Friedman two-way analysis of variance by ranks In Section I it is noted that **Kendall's coefficient of concordance** and the **Friedman two-way analysis of variance by ranks** are based on the same mathematical model. Equation 31.8 defines the relationship between the computed value of \tilde{W} and χ_r^2 . The chi-square value (χ_r^2) in Equation 31.8 can be employed to represent the test statistic for the **Friedman two-way analysis of variance by ranks** (which is more commonly computed with Equation 25.1). Note that Equation 31.8 is identical to Equation 31.5.

$$\chi_r^2 = m(n - 1)\tilde{W} \quad \text{(Equation 31.8)}$$

Equation 31.9, which is the algebraic transposition of Equation 31.8, provides an alternative way of computing the value \tilde{W} .

$$\tilde{W} = \frac{\chi_r^2}{m(n - 1)} \quad \text{(Equation 31.9)}$$

In order to employ Equation 31.9 to compute the value of \tilde{W} , it is necessary to evaluate the data for m sets of ranks on n subjects/objects with the **Friedman two-way analysis of variance by ranks**. To illustrate the equivalence of **Kendall's coefficient of concordance** and the **Friedman two-way analysis of variance by ranks**, consider Example 31.3 which employs the same variables employed in Example 25.1 (which is used to illustrate the **Friedman two-way analysis of variance by ranks**). Note that in Example 31.3 there are $m = 6$ judges (who are represented by the six subjects) and $n = 3$ objects (which are represented by the three levels of noise).

Example 31.3 *Six subjects rank three levels of noise (based on the presence or absence of different types of music) with respect to the degree they believe each level of noise will disrupt one's ability to learn a list of nonsense syllables. The subjects are instructed to assign a rank of 1 to the most disruptive level of noise and a rank of 3 to the least disruptive level of noise. Table 31.4 summarizes the rankings of the subjects. Is there a significant association between the rank-orders assigned to the three levels of noise by the six subjects?*

Employing Equation 31.4, the value $\tilde{W} = .92$ is computed.⁷ The value $\tilde{W} = .92$ indicates a strong degree of association between the six sets of ranks.

$$\tilde{W} = \frac{(12)(498.5) - (3)(6)^2(3)(3 + 1)^2}{(6)^2(3)[(3)^2 - 1]} = .92$$

Table 31.4 Data for Example 31.3

Subject	Type of noise			Totals
	No noise	Classical music	Rock music	
1	3	2	1	
2	3	2	1	
3	3	2	1	
4	3	2	1	
5	3	2	1	
6	3	1.5	1.5	
ΣR_j	18	11.5	6.5	$T = 36$
$(\Sigma R_j)^2$	324	132.25	42.25	$U = 498.5$

It happens to be the case that the configuration of ranks in Example 31.3 is identical to the configuration of ranks employed in Example 25.1. When the **Friedman two-way analysis of variance by ranks** is employed to evaluate the same six sets of ranks, the value $\chi_r^2 = 11.08$ is computed. The reader should take note of the fact that when the data are evaluated with Equation 25.1 in Section IV of the **Friedman test**, k is employed to represent the number of levels of the independent variable and n is employed to represent the number of subjects. In Table 25.1, the three columns of R_j values represent the $k = 3$ levels of the independent variable, and the six rows represent the $n = 6$ subjects. In the model employed for **Kendall's coefficient of concordance**, the value of n corresponds to the value employed for k in the **Friedman model**, and thus, $n = k = 3$. The value of m in the **Kendall model** corresponds to the value employed for n in the **Friedman model**, and thus, $m = n = 6$. The equations used in this section employ notation that is consistent with the **Kendall model**.

When the value $\chi_r^2 = 11.08$ is substituted in Equation 31.9, the value $\tilde{W} = .92$ is computed.

$$\tilde{W} = \frac{11.08}{(6)(3 - 1)} = .92$$

In the same respect, if $\tilde{W} = .92$ is substituted in Equations 31.8/31.5, it yields the value $\chi_r^2 = 11.08$.⁸

$$\chi_r^2 = (6)(3 - 1)(.92) = 11.08$$

Since the value of \tilde{W} can be computed for the **Friedman test** model, **Kendall's coefficient of concordance** can be employed as a measure of effect size for a within-subjects design (involving data that are rank-ordered) with an independent variable that has three or more levels. The closer the value of \tilde{W} is to 1, the stronger the relationship between the independent and dependent variables. Consequently, the value $\tilde{W} = .92$ computed for Example 25.1 (as well as Example 31.3), indicates there is a strong degree of association between the independent

variable (noise) and the dependent variable (the rank-ordering on number of nonsense syllables recalled/disruptive potential of noise).

3. Weighted rank/top-down concordance Section VII of **Spearman's rank-order correlation coefficient** briefly discusses a method referred to as **weighted/top-down correlation** that can be employed for differentially weighting the most extreme scores in a set of data. Zar (1999, pp. 449–450) describes the extension of this method to **Kendall's coefficient of concordance**. Thus, a **weighted/top-down correlation coefficient** can be employed if a researcher's primary concern is with the degree of agreement for objects/subjects that are ranked the highest by a set of judges. In such a case the correlation coefficient would minimally weight scores of a lower rank.

VIII. Additional Examples Illustrating the Use of Kendall's Coefficient of Concordance

Examples 31.4 and 31.5 are two additional examples that can be evaluated with **Kendall's coefficient of concordance**. Example 31.4 addresses the same question evaluated by Example 29.2, but in Example 31.4 the values $m = 6$ and $n = 4$ are employed in place of the values $m = 2$ and $n = 10$ employed in Example 29.2. Since Examples 31.4 and 31.5 employ the same data as Example 31.1, they yield the same result.

Example 31.4 *In order to determine whether critics agree with one another in their evaluation of movies, a newspaper editor asks six critics to rank four movies (assigning a rank of 1 to the best movie, a rank of 2 to the next best movie, etc.). Table 31.5 summarizes the data for the study. Is there a significant association between the six sets of ranks?*

Table 31.5 Data for Example 31.4

Critic	Movie				Totals
	1	2	3	4	
1	3	2	1	4	
2	3	2	1	4	
3	3	2	1	4	
4	4	2	1	3	
5	3	2	1	4	
6	4	1	2	3	
ΣR_j	20	11	7	22	$T = 60$
$(\Sigma R_j)^2$	400	121	49	484	$U = 1054$

Example 31.5 *Four members of a track team are ranked by the head coach with respect to their ability on six track and field events. For each event, the coach assigns a rank of 1 to the athlete who is best at the event and a rank of 4 to the athlete who is worst at the event. Table 31.6 summarizes the data for the study. Is there a significant association between the rank-orders assigned to the athletes on the six events?*

Note that in Example 31.5, even though one judge (the coach) is employed, the judge generates six sets of ranks (i.e., six sets of judgements). If there is a significant association between the six sets of ranks/judgements, it indicates that the athletes are perceived to be consistent with respect to performance on the six events.

Table 31.6 Data for Example 31.5

Event	Athlete				Totals
	1	2	3	4	
Sprint	3	2	1	4	
1500 meters	3	2	1	4	
Pole vault	3	2	1	4	
Long jump	4	2	1	3	
Shot put	3	2	1	4	
400 meters	4	1	2	3	
ΣR_j	20	11	7	22	$T = 60$
$(\Sigma R_j)^2$	400	121	49	484	$U = 1054$

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Endnotes

1. Siegel and Castellan (1988) emphasize the fact that a correlation equal to or close to 1 does not in itself indicate that the rankings are correct. A high correlation only indicates that there is agreement among the m sets of ranks. It is entirely possible that there can be complete agreement among two or more sets of ranks, but that all of the rankings are, in fact, incorrect. In other words, the ranks may not reflect what is actually true with regard to the subjects/objects that are evaluated.
2. In point of fact, if the values of r_s and \tilde{W} are computed for $m = 2$ sets of ranks, when the

computed values for r_s are, respectively, 1, -1, and 0 the computed values of \tilde{W} will, respectively, be 1, 0, and .5. The latter sets of values can be obtained through use of Equation 31.7, which is presented in Section VII.

3. Some sources state that the alternative hypothesis is **directional**, since \tilde{W} can only be a positive value. Related to this is the fact that only the upper tail of the chi-square distribution (which is discussed in Section V) is employed in approximating the exact sampling distribution of \tilde{W} . In the final analysis, it becomes academic whether one elects to identify the alternative hypothesis as directional or nondirectional.
4. The tie-corrected version of Equation 31.3 is noted below:

$$\tilde{W} = \frac{S}{\left(\frac{m^2 n (n^2 - 1) - m \sum_{i=1}^m \left[\sum_{a=1}^s (t_a^3 - t_a) \right]}{12} \right)} = \frac{35}{\left(\frac{(4)^2(4)[(4)^2 - 1] - (4)(36)}{12} \right)} = .51$$

5. Note that for $m = 3$ and $n = 3$, no tabled critical values are listed in [Table A20](#). This is the case, since critical values cannot be computed for values of m and n that fall below specific minimum values. If Equation 31.5 is employed to evaluate $\tilde{W} = .111$, it yields the following result: $\chi^2 = (3)(3 - 1)(.111) = .666$. Since $\chi^2 = .666$ is less than the tabled critical two-tailed value (for $df = 2$) $\chi_{.05}^2 = 5.99$, the obtained value $\tilde{W} = .111$ is not significant. In point of fact, even if the maximum possible value $\tilde{W} = 1$ is substituted in Equation 31.5, it yields the value $\chi^2 = 6$, which is barely above $\chi_{.05}^2 = 5.99$. Since the chi-square distribution provides an approximation of the exact sampling distribution, in this instance it would appear that the tabled value $\chi_{.05}^2 = 5.99$ is a little too high and, in actuality, is associated with a Type I error rate that is slightly above .05.
6. The summary of the data for Example 29.2 in [Table 29.6](#) provides the necessary values required to compute the value of \tilde{W} . The latter values are not computed in [Table 29.5](#), which (employing a different format) also summarizes the data for Example 29.2.
7. Although there is one set of ties in the data, the tie correction described in Section VI is not employed for Example 31.3.
8. The exact value $\chi_r^2 = 11.08$ is computed if the value $\tilde{W} = .9236$ (which carries the computation of \tilde{W} to four decimal places) is employed in Equations 31.8/31.5.

Test 32

Goodman and Kruskal's Gamma (Nonparametric Measure of Association/Correlation Employed with Ordinal Data)

I. Hypothesis Evaluated with Test and Relevant Background Information

Goodman and Kruskal's gamma is one of a number of measures of correlation or association discussed in this book. Measures of correlation are not inferential statistical tests, but are, instead, descriptive statistical measures that represent the degree of relationship between two or more variables. Upon computing a measure of correlation, it is common practice to employ one or more inferential statistical tests in order to evaluate one or more hypotheses concerning the correlation coefficient. The hypothesis stated below is the most commonly evaluated hypothesis for **Goodman and Kruskal's gamma**.

Hypothesis evaluated with test In the underlying population represented by a sample, is the correlation between subjects' scores on two variables some value other than zero?

Relevant background information on test Prior to reading the material in this section the reader should review the general discussion of correlation in Section I of the **Pearson product-moment correlation coefficient (Test 28)**, as well as the material in Section I of **Kendall's tau (Test 30)**. Developed by Goodman and Kruskal (1954, 1959, 1963, 1972), **gamma** is a bivariate measure of correlation/association that is employed with rank-order data which is summarized within the format of an **ordered contingency table**. The population parameter estimated by the correlation coefficient will be represented by the notation γ (which is the lower case Greek letter **gamma**). The sample statistic computed to estimate the value of γ will be represented by the notation G . As is the case with **Spearman's rank-order correlation coefficient (Test 29)** and **Kendall's tau**, **Goodman and Kruskal's gamma** can be employed to evaluate data in which a researcher has scores for n subjects/objects on two variables (designated as the X and Y variables), both of which have been rank-ordered. However, in contrast to **Spearman's rho** and **Kendall's tau**, computation of **gamma** is recommended when there are many ties in a set of data, and thus it becomes more efficient to summarize the data within the format of an ordered $r \times c$ contingency table.

An ordered $r \times c$ contingency table consists of $r \times c$ cells, and is comprised of r rows and c columns.¹ In the model employed for **Goodman and Kruskal's gamma**, each of the rows in the contingency table represents one of the r levels of the X variable, and each of the columns represents one of the c levels of the Y variable (or vice versa). Since the contingency table that is employed to summarize the data is ordered, the categories for both the row and the column variables are arranged sequentially with respect to magnitude/ordinal position. To be more specific, the first row in the table represents the category that is lowest in magnitude on the X variable and the r^{th} row represents the category that is highest in magnitude on the X variable. In the same respect, the first column represents the category that is lowest in magnitude on the Y

variable and the c^{th} column represents the category that is highest in magnitude on the Y variable.² Recorded within each of the $r \times c$ cells of the contingency table are the number of subjects whose categorization on the X and Y variables corresponds to the row and column of a specific cell.

The value of **gamma** computed for a set of data represents the difference $p(C) - p(D)$, where: a) $p(C)$ is the probability that the ordering of the scores on the row and column variables for a pair of subjects is concordant (i.e., in agreement); and b) $p(D)$ is the probability that the ordering of the scores on the row and column variables for a pair of subjects is discordant (i.e., disagree).

To illustrate, if a subject is categorized on the lowest level of the row variable and the highest level of the column variable, that subject is concordant with respect to ordering when compared with any other subject who is assigned to a lower category on the row variable than he is on the column variable. On the other hand, that subject is discordant with respect to ordering when compared with another subject who is assigned to a higher category on the row variable than he is on the column variable. For a more thorough discussion of the concepts of concordance and discordance the reader should review Section I of **Kendall's tau**.

The range of possible values within which a computed value of **gamma** may fall is $-1 \leq G \leq +1$. As is the case for **Kendall's tau**, a positive value of G indicates that the number of concordant pairs in a set of data is greater than the number of discordant pairs, while a negative value indicates that the number of discordant pairs is greater than the number of concordant pairs. The computed value of G will equal 1 when the ordering of scores for all of the pairs of subjects in a set of data is concordant, and will equal -1 when the ordering of scores for all of the pairs of subjects is discordant. When $G = 0$, the number of concordant and discordant pairs of subjects in a set of data is equal.

Since **Goodman and Kruskal's gamma** and **Kendall's tau** both involve evaluating pairs of scores with respect to concordance versus discordance, the two measures of association are related to one another. Marascuilo and McSweeney (1977), who provide a detailed discussion on the nature of the relationship between **gamma** and **tau**, note that if $\bar{\tau}$ and G are computed for the same set of data, as the number of pairs of ties increase, the absolute value computed for G will become increasingly larger relative to the absolute value of $\bar{\tau}$. As a result of the latter, researchers who want to safeguard against obtaining an inflated value for the degree of association between the two variables may prefer to compute $\bar{\tau}$ for a set of rank-order data, as opposed to computing the value of G .

It should be noted that **Yule's Q (Test 16i)** (which is one of a number of measures of association that can only be employed to evaluate a 2×2 contingency table) represents a special case of **Goodman and Kruskal's gamma**. Although **gamma** can be employed with a 2×2 contingency table, it is typically employed with ordered contingency tables in which there are at least three levels on either the row or column variable. A more detailed discussion of the relationship between **Yule's Q** and **Goodman and Kruskal's gamma** can be found in Section VII.

II. Example

Example 32.1 *A researcher wants to determine whether or not a relationship exists between a person's weight (which will be designated as the X variable) and birth order (which will be designated as the Y variable). Upon determining the weight and birth order of 300 subjects, each subject is categorized with respect to one of three weight categories and one of four birth order categories. Specifically, the following three categories are employed with respect to weight: **below average, average, above average**. The following four categories are employed with respect to birth order: **first born, second born, third born, fourth born and all subsequent***

birth orders. Table 32.1 (which is a 3×4 ordered contingency table, with $r = 3$ and $c = 4$) summarizes the data. Do the data indicate there is a significant association between a person's weight and birth order?

Table 32.1 Summary of Data for Example 32.1

		Birth order				Row sums
		1st born	2nd born	3rd born	4th born+	
Weight	Below average	70	15	10	5	100
	Average	10	60	20	10	100
	Above average	10	15	35	40	100
Column sums		90	90	65	55	300

III. Null versus Alternative Hypotheses

Upon computing **Goodman and Kruskal's gamma**, it is common practice to determine whether the obtained absolute value of the correlation coefficient is large enough to allow a researcher to conclude that the underlying population correlation coefficient between the two variables is some value other than zero. Section V describes how the latter hypothesis, which is stated below, can be evaluated through use of an inferential statistical test that is based on the normal distribution.

Null hypothesis

$$H_0: \gamma = 0$$

(In the underlying population the sample represents, the correlation between the scores/categorization of subjects on Variable X and Variable Y equals 0.)

Alternative hypothesis

$$H_1: \gamma \neq 0$$

(In the underlying population the sample represents, the correlation between the scores/categorization of subjects on Variable X and Variable Y equals some value other than 0. This is a **nondirectional alternative hypothesis**, and it is evaluated with a **two-tailed test**. Either a significant positive G value or a significant negative G value will provide support for this alternative hypothesis. In order to be significant, the obtained absolute value of G must be equal to or greater than the tabled critical two-tailed G value at the prespecified level of significance.)

or

$$H_1: \gamma > 0$$

(In the underlying population the sample represents, the correlation between the scores/categorization of subjects on Variable X and Variable Y equals some value greater than 0. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. Only a significant positive G value will provide support for this alternative hypothesis. In order to be significant (in addition to the requirement of a positive G value), the obtained absolute value of G must be equal to or greater than the tabled critical one-tailed G value at the prespecified level of significance.)

or

$$H_1: \gamma < 0$$

(In the underlying population the sample represents, the correlation between the scores/

categorization of subjects on Variable X and Variable Y equals some value less than 0. This is a **directional alternative hypothesis**, and it is evaluated with a **one-tailed test**. Only a significant negative G value will provide support for this alternative hypothesis. In order to be significant (in addition to the requirement of a negative G value), the obtained absolute value of G must be equal to or greater than the tabled critical one-tailed G value at the prespecified level of significance.)

Note: Only one of the above noted alternative hypotheses is employed. If the alternative hypothesis the researcher selects is supported, the null hypothesis is rejected.³

IV. Test Computations

In order to compute the value of G , it is necessary to determine the number of pairs of subjects who are concordant with respect to the ordering of their scores on the X and Y variables (which will be represented by the notation n_C), and the number of pairs of subjects who are discordant with respect to the ordering of their scores on the X and Y variables (which will be represented by the notation n_D). Upon computing the values of n_C and n_D , Equation 32.1 is employed to compute the value of **Goodman and Kruskal's gamma**.

$$G = \frac{n_C - n_D}{n_C + n_D} \quad \text{(Equation 32.1)}$$

The determination of the values of n_C and n_D is based on an analysis of the frequencies in the ordered contingency table (i.e., Table 32.1). Each of the cells in the table will be identified by two digits. The first digit will represent the row within which the cell falls, and the second digit will represent the column within which the cell falls. Thus, Cell _{ij} is the cell in the i^{th} row and j^{th} column. As an example, since it is in both the first row and first column, the cell in the upper left hand corner of Table 32.1 is Cell₁₁. The number of subjects within each cell is identified by the notation n_{ij} . Thus, in the case of Cell₁₁, $n_{11} = 70$.

The protocol for determining the values of n_C and n_D will now be described. The following procedure is employed to determine the value of n_C .

a) Begin with the cell in the **upper left hand corner of the table** (i.e., Cell₁₁). Determine the frequency of that cell (which will be referred to as the target cell), and multiply the frequency by the sum of the frequencies of **all other cells in the table that fall both below it and to the right of it**. In Table 32.1, the following six cells meet the criteria of being both below and to the right of Cell₁₁: Cell₂₂, Cell₂₃, Cell₂₄, Cell₃₂, Cell₃₃, Cell₃₄. Note that although Cell₂₁ and Cell₃₁ are below Cell₁₁, they are not to the right of it, and although Cell₁₂, Cell₁₃, and Cell₁₄ fall to the right of Cell₁₁, they do not fall below it. Any subject who falls within a cell that is both below and to the right of Cell₁₁ will form a concordant pair with any subject in Cell₁₁. The rationale for this is as follows: Assume that the values R_{X_i} and R_{Y_i} represent the score/ranking/category of Subject i on the X and Y variables, and that R_{X_j} and R_{Y_j} represent the score/ranking/category of Subject j on the X and Y variables. Assume that Subject i is a subject in the target cell, and that Subject j is a subject in a cell that falls below and to the right of the target cell. We can state that the sign of the difference ($R_{X_i} - R_{X_j}$) will be the same as the sign of the difference ($R_{Y_i} - R_{Y_j}$) when the scores of any subject in the target cell are compared with any subject in a cell that falls below and to the right of the target cell. When for any pair of subjects the signs of the differences ($R_{X_i} - R_{X_j}$) and ($R_{Y_i} - R_{Y_j}$) are identical, that pair of subjects is concordant with respect to their ordering on the two variables.

To illustrate, each of the 70 subjects in Cell₁₁ has a rank of 1 on both of the variables, and each of the 60 subjects in Cell₂₂ (which is one of the cells below and to the right of Cell₁₁) has a rank of 2 on both of the variables. Any pair of subjects that is formed by employing one subject from Cell₁₁ and one subject from Cell₂₂ will be concordant with respect to their ordering on the two variables, since for each pair the sign of the difference between the ranks on both variables will be negative (i.e., $(R_{X_i} - R_{X_j}) = (1 - 2) = -1$ and $(R_{Y_i} - R_{Y_j}) = (1 - 2) = -1$). If, on the other hand, we compare the ranks on both variables for any subject who is in the target cell with the ranks on both variables for any subject who is in a cell that is not below and to the right of the target cell, $(R_{X_i} - R_{X_j})$ and $(R_{Y_i} - R_{Y_j})$ will have different signs or will equal zero.

The expression which summarizes the product of the frequency of Cell₁₁ and the sum of the frequencies of all the cells that fall both below and to the right of it is as follows: $n_{11}(n_{22} + n_{23} + n_{24} + n_{32} + n_{33} + n_{34})$. Substituting the appropriate frequencies from Table 32.1, we obtain $70(60 + 20 + 10 + 15 + 35 + 40) = (70)(180) = 12600$. This latter value will be designated as **Product 1**.

b) The same procedure employed with Cell₁₁ is applied to all remaining cells. Moving to the right in Row 1, the procedure is next employed with Cell₁₂. **Product 2**, which represents the product for the second target cell, can be summarized by the expression $n_{12}(n_{23} + n_{24} + n_{33} + n_{34})$, since Cell₂₃, Cell₂₄, Cell₃₃, and Cell₃₄ are the only cells that fall both below and to the right of Cell₁₂. Thus, **Product 2** will equal $15(20 + 10 + 35 + 40) = (15)(105) = 1575$.

c) Upon computing **Product 2**, products for the two remaining cells in Row 1 are computed, after which products are computed for each of the cells in Rows 2 and 3. The computation of the products for all 12 cells in the ordered contingency table is summarized in Table 32.2. Note that since many of the cells have no cell that falls both below and to the right of them, the value that the frequency of these cells will be multiplied by will equal zero, and thus the resulting product will equal zero. The value of n_C is the sum of all the products in Table 32.2. For Example 32.1, $n_C = 20875$.

Table 32.2 Computation of n_C for Example 32.1

Cell ₁₁ : 70 (60 + 20 + 10 + 15 + 35 + 40)	=	12600	Product 1
Cell ₁₂ : 15 (20 + 10 + 35 + 40)	=	1575	Product 2
Cell ₁₃ : 10 (10 + 40)	=	500	Product 3
Cell ₁₄ : 5 (0)	=	0	Product 4
Cell ₂₁ : 10 (15 + 35 + 40)	=	900	Product 5
Cell ₂₂ : 60 (35 + 40)	=	4500	Product 6
Cell ₂₃ : 20 (40)	=	800	Product 7
Cell ₂₄ : 10 (0)	=	0	Product 8
Cell ₃₁ : 10 (0)	=	0	Product 9
Cell ₃₂ : 15 (0)	=	0	Product 10
Cell ₃₃ : 35 (0)	=	0	Product 11
Cell ₃₄ : 40 (0)	=	0	Product 12
$n_C = \text{Sum of products} =$			20875

Upon computing the value of n_C , the following protocol is employed to compute the value of n_D .

a) Begin with the cell in the **upper right hand corner of the table** (i.e., Cell₁₄). Determine the frequency of that cell, and multiply the frequency by the sum of the frequencies of **all other cells in the table that fall both below it and to the left of it**. In Table 32.1, the following six cells meet the criteria of being both below and to the left of Cell₁₄: Cell₂₁, Cell₂₂, Cell₂₃, Cell₃₁, Cell₃₂, Cell₃₃. Note that although Cell₂₄ and Cell₃₄ are below Cell₁₄, they are not to the left of it,

and although Cell₁₁, Cell₁₂, and Cell₁₃ fall to the left of Cell₁₄, they do not fall below it. Any subject who falls within a cell that is both below and to the left of Cell₁₄ will form a discordant pair with any subject in Cell₁₄. The general rule that can be stated with respect to discordant pairs is as follows (if we assume that Subject i is a subject in the target cell, and Subject j is a subject in some other cell): The sign of the difference $(R_{X_i} - R_{X_j})$ will be different than the sign of the difference $(R_{Y_i} - R_{Y_j})$ when the scores of any subject in the target cell are compared with any subject in a cell that falls below and to the left of the target cell. When for any pair of subjects the signs of the differences $(R_{X_i} - R_{X_j})$ and $(R_{Y_i} - R_{Y_j})$ are different, that pair of subjects is discordant with respect to their ordering on the two variables.

To illustrate, each of the 5 subjects in Cell₁₄ has a rank of 1 on weight and a rank of 4 on birth order. Each of the 20 subjects in Cell₂₃ (which is one of the cells below and to the left of Cell₁₄) has a rank of 2 on weight and a rank of 3 on birth order. Any pair of subjects that is formed by employing one subject from Cell₁₄ and one subject from Cell₂₃, will be discordant with respect to the ordering of the ranks of the subjects on the two variables, since for each pair the signs of the difference between the ranks on both variables will be different (i.e., $(R_{X_i} - R_{X_j}) = (1 - 2) = -1$ and $(R_{Y_i} - R_{Y_j}) = (4 - 3) = +1$). If, on the other hand, we compare the ranks on both variables for any subject who is in the target cell with the ranks on both variables for any subject who is in a cell that is not below and to the left of the target cell, $(R_{X_i} - R_{X_j})$ and $(R_{Y_i} - R_{Y_j})$ will have the same sign or will equal zero.

The expression which summarizes the product of the frequency of Cell₁₄ and the sum of the frequencies of all cells that fall both below it and to the left of it is as follows: $n_{14}(n_{21} + n_{22} + n_{23} + n_{31} + n_{32} + n_{33})$. Substituting the appropriate frequencies, we obtain $5(10 + 60 + 20 + 10 + 15 + 35) = (5)(150) = 750$. As is the case in determining the number of concordant pairs, we will designate the product for the first cell that is analyzed as **Product 1**.

b) The same procedure employed with Cell₁₄ is applied to all remaining cells. Moving to the left in Row 1, the procedure is next employed with Cell₁₃. **Product 2**, which represents the product for the second target cell, can be summarized by the expression $n_{13}(n_{21} + n_{22} + n_{31} + n_{32})$, since Cell₂₁, Cell₂₂, Cell₃₁, and Cell₃₂ are the only cells that fall both below and to the left of Cell₁₃. Thus, **Product 2** will equal $10(10 + 60 + 10 + 15) = (10)(95) = 950$.

c) Upon computing **Product 2**, products for the two remaining cells in Row 1 are computed, after which products are computed for each of the cells in Rows 2 and 3. The computation of the products for all 12 cells in the ordered contingency table is summarized in Table 32.3. Note that since many of the cells have no cell that falls both below and to the left of them, the value that the

Table 32.3 Computation of n_D for Example 32.1

Cell ₁₄ : 5 (10 + 60 + 20 + 10 + 15 + 35)	= 750	Product 1
Cell ₁₃ : 10 (10 + 60 + 10 + 5)	= 950	Product 2
Cell ₁₂ : 15 (10 + 10)	= 300	Product 3
Cell ₁₁ : 70 (0)	= 0	Product 4
Cell ₂₄ : 10 (10 + 15 + 35)	= 600	Product 5
Cell ₂₃ : 20 (10 + 15)	= 500	Product 6
Cell ₂₂ : 60 (10)	= 600	Product 7
Cell ₂₁ : 10 (0)	= 0	Product 8
Cell ₃₄ : 40 (0)	= 0	Product 9
Cell ₃₃ : 35 (0)	= 0	Product 10
Cell ₃₂ : 15 (0)	= 0	Product 11
Cell ₃₁ : 10 (0)	= 0	Product 12
$n_D = \text{Sum of products} =$		3700

frequency of such cells will be multiplied by will equal zero, and thus the resulting product will equal zero. The value of n_D will be the sum of all the products in Table 32.3. For Example 32.1, $n_D = 3700$.

Substituting the values $n_C = 20875$ and $n_D = 3700$ in Equation 32.1, the value $G = .70$ is computed. Note that the value of G is positive, since the number of concordant pairs is greater than the number of discordant pairs.

$$G = \frac{20875 - 3700}{20875 + 3700} = .70$$

The value $G = .70$ can also be computed employing the definition of **gamma** presented in Section I. Specifically:

$$G = p(C) - p(D) = \frac{20875}{24575} - \frac{3700}{24575} = .70$$

In the above equation the value 24575 is the total number of pairs (to be designated n_T), which is the denominator of Equation 32.1. Thus, $p(C) = n_C/n_T$ and $p(D) = n_D/n_T$.

Since the computed value $G = .70$ is close to 1, it indicates the presence of a strong positive/direct relationship between the two variables. Specifically, it suggests that the higher the rank of a subject's weight category, the higher the rank of the subject's birth order category.

V. Interpretation of the Test Results

Test 32a: Test of significance for Goodman and Kruskal's gamma When the sample size is relatively large (which will generally be the case when **gamma** is computed), the computed value of G can be evaluated with Equation 32.2. To be more specific, Equation 32.2 (which employs the normal distribution) is employed to evaluate the null hypothesis $H_0: \gamma = 0$.⁴ The sign of the z value computed with Equation 32.2 will be the same as the sign of the value computed for G .

$$z = G \sqrt{\frac{n_C + n_D}{N(1 - G^2)}} \quad (\text{Equation 32.2})$$

Where: N is the total number of subjects for whom scores are recorded in the ordered contingency table

When the appropriate values from Example 32.1 are substituted in Equation 32.2, the value $z = 8.87$ is computed.

$$z = .70 \sqrt{\frac{20875 + 3700}{300[1 - (.70)^2]}} = 8.87$$

Equation 32.3 is an alternative equation for computing the value of z . The denominator of Equation 32.3 represents the **standard error** of the G statistic (which will be represented by the notation SE_G). In Section VI, SE_G is employed to compute a confidence interval for **gamma**.

(Equation 32.3)

$$z = \frac{G}{SE_G} = \frac{G}{\sqrt{\frac{1}{\frac{n_C + n_D}{N(1 - G^2)}}}} = \frac{.70}{\sqrt{\frac{1}{\frac{20875 + 3700}{(300)[1 - (.70)^2]}}} = \frac{.70}{.0789} = 8.87$$

The computed value $z = 8.87$ is evaluated with **Table A1 (Table of the Normal Distribution)** in the **Appendix**.⁵ In the latter table, the tabled critical two-tailed .05 and .01 values are $z_{.05} = 1.96$ and $z_{.01} = 2.58$, and the tabled critical one-tailed .05 and .01 values are $z_{.05} = 1.65$ and $z_{.01} = 2.33$.

The following guidelines are employed in evaluating the null hypothesis.

a) If the nondirectional alternative hypothesis $H_1: \gamma \neq 0$ is employed, the null hypothesis can be rejected if the obtained absolute value of z is equal to or greater than the tabled critical two-tailed value at the prespecified level of significance.

b) If the directional alternative hypothesis $H_1: \gamma > 0$ is employed, the null hypothesis can be rejected if the sign of z is positive, and the value of z is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

c) If the directional alternative hypothesis $H_1: \gamma < 0$ is employed, the null hypothesis can be rejected if the sign of z is negative, and the absolute value of z is equal to or greater than the tabled critical one-tailed value at the prespecified level of significance.

Employing the above guidelines, the nondirectional alternative hypothesis $H_1: \gamma \neq 0$ is supported at both the .05 and .01 levels, since the computed value $z = 8.87$ is greater than the tabled critical two-tailed values $z_{.05} = 1.96$ and $z_{.01} = 2.58$. The directional alternative hypothesis $H_1: \gamma > 0$ is supported at both the .05 and .01 levels, since the computed value $z = 8.87$ is a positive number that is greater than the tabled critical one-tailed values $z_{.05} = 1.65$ and $z_{.01} = 2.33$. The directional alternative hypothesis $H_1: \gamma < 0$ is not supported, since the computed value $z = 8.87$ is a positive number.

A summary of the analysis of Example 32.1 follows: It can be concluded that there is a significant positive relationship between weight and birth order.

VI. Additional Analytical Procedures for Goodman and Kruskal's Gamma and/or Related Tests

1. The computation of a confidence interval for the value of Goodman and Kruskal's gamma Equation 32.4 is employed to compute a confidence interval for a computed value of gamma.

$$CI_{(1-\alpha)} = G \pm (z_{\alpha/2})(SE_G) \quad (\text{Equation 32.4})$$

Where: $z_{\alpha/2}$ represents the tabled critical two-tailed value in the normal distribution below which a proportion (percentage) equal to $[1 - (\alpha/2)]$ of the cases falls. If the proportion (percentage) of the distribution that falls within the confidence interval is subtracted from 1 (100%), it will equal the value of α .

Equation 32.4 will be employed to compute the 95% confidence interval for **gamma**. Along with the tabled critical two-tailed .05 value $z_{.05} = 1.96$, the following values computed for Example 32.1 are substituted in Equation 32.4: $G = .70$ and $SE_G = .0789$ (which is the

computed value of the denominator of Equation 32.3, which as noted in Section V represents the **standard error** of G).

$$CI_{.95} = .70 \pm (1.96)(.0789) = .70 \pm .15$$

Subtracting from and adding .15 to .70, yields the values .55 and .85. Thus, the researcher can be 95% confident (or the probability is .95) that the true value of **gamma** in the underlying population falls between .55 and .85. Symbolically, this can be written as follows: $.55 \leq \gamma \leq .85$.

2. Test 32b: Test for evaluating the null hypothesis $H_0: \gamma_1 = \gamma_2$ Marascuilo and McSweeney (1977) note that Equation 32.5 can be employed to determine whether or not there is a significant difference between two independent values of **gamma**. Use of Equation 32.5 assumes that the following conditions have been met: a) The sample size in each of two ordered contingency tables is large enough for evaluation with the normal approximation; b) The values of r and c are identical in the two ordered contingency tables; and c) The same row and column categories are employed in the two ordered contingency tables.

$$z = \frac{G_1 - G_2}{\sqrt{SE_{G_1} + SE_{G_2}}} \quad (\text{Equation 32.5})$$

Where: G_1 and G_2 are the computed values of **gamma** for the two ordered contingency tables, and SE_{G_1} and SE_{G_2} are the computed values of the **standard error** for the two values of **gamma**

To illustrate the use of Equation 32.5, assume that the study described in Example 32.1 is replicated with a different sample comprised of $N = 600$ subjects. The obtained value of **gamma** for the sample is $G = .50$, with $SE_G = .0438$. By employing the values $G_1 = .70$, $SE_{G_1} = .0789$, $G_2 = .50$, and $SE_{G_2} = .0438$ in Equation 32.5, the researcher can evaluate the null hypothesis $H_0: \gamma_1 = \gamma_2$. Substituting the appropriate values in Equation 32.5 yields the value $z = .57$.

$$z = \frac{.7 - .5}{\sqrt{.0789 + .0438}} = .57$$

The same guidelines described for evaluating the alternative hypotheses $H_1: \gamma \neq 0$, $H_1: \gamma > 0$, and $H_1: \gamma < 0$ are, respectively, employed for evaluating the alternative hypotheses $H_1: \gamma_1 \neq \gamma_2$, $H_1: \gamma_1 > \gamma_2$, and $H_1: \gamma_1 < \gamma_2$. The nondirectional alternative hypothesis $H_1: \gamma_1 \neq \gamma_2$ is not supported, since the computed value $z = .57$ is less than the tabled critical two-tailed value $z_{.05} = 1.96$. The directional alternative hypothesis $H_1: \gamma_1 > \gamma_2$ is not supported, since the computed value $z = .57$ is less than the tabled critical one-tailed value $z_{.05} = 1.65$. The directional alternative hypothesis $H_1: \gamma_1 < \gamma_2$ is not supported, since the computed value $z = .57$ is a positive number. The fact that the difference $\gamma_1 - \gamma_2 = .7 - .5 = .2$ (which is reasonably large) is not significant, can be attributed to the fact that both samples have relatively large standard errors.

3. Sources for computing a partial correlation coefficient for Goodman and Kruskal's gamma A procedure developed by Davis (1967) for computing a partial correlation for **gamma** is described in Marascuilo and McSweeney (1977).

VII. Additional Discussion of Goodman and Kruskal's Gamma

1. Relationship between Goodman and Kruskal's gamma and Yule's Q In Section I it is noted that **Yule's Q** is a special case of **Goodman and Kruskal's gamma**. To illustrate this, assume that the four cells in [Tables 16.2/16.3](#) (for which **Yule's Q** is computed) represent a 2×2 contingency table in which the cells on both the row and the column variables are ordered. If the procedure described for determining concordant pairs is employed with the data in [Tables 16.2/16.3](#), the only cell that will generate a product other than zero is Cell₁₁ (which corresponds to **Cell a** within the framework of the notation used for a 2×2 contingency table). Specifically, the product for Cell₁₁, which will correspond to the value of n_C , is $(n_{11})(n_{12}) = (30)(40) = 1200$. In the same respect, if the procedure described for determining discordant pairs is employed, the only cell that will generate a product other than zero is Cell₁₂ (which corresponds to **Cell b** within the framework of the notation used for a 2×2 contingency table). Specifically, the product for Cell₁₂, which will correspond to the value of n_D , is $(n_{12})(n_{21}) = (70)(60) = 4200$. When the values $n_C = 1200$ and $n_D = 4200$ are substituted in Equation 32.1, $G = (1200 - 4200)/(1200 + 4200) = -.56$. Note that this result is identical to that obtained when Equation 16.20 is employed to compute **Yule's Q** for the same set of data: $Q = (ad - bc)/(ad + bc) = [(30)(40) - (70)(60)]/[(30)(40) + (70)(60)] = -.56$. It should be noted that unlike **gamma**, which is only employed with ordered contingency tables, **Yule's Q** can be employed with both ordered and unordered 2×2 contingency tables.

2. Somers' delta as an alternative measure of association for an ordered contingency table Somers (1962) has developed an alternative measure of association for ordered contingency tables referred to as **delta** (which is represented by the upper case Greek letter Δ). Siegel and Castellan (1988) identify **delta** as an **asymmetrical measure of association** (as opposed to a **symmetrical measure of association**). An asymmetrical measure of association is employed when one variable is distinguished in a meaningful way from the other variable (e.g., within the context of the study, one variable is more important than the other, or one variable represents an independent variable and the other a dependent variable). Within this framework, **gamma** is viewed as a symmetrical measure of association, since it does not assume a meaningful distinction between the variables within the context noted above. A full discussion of **Somers' delta** can be found in Siegel and Castellan (1988).

VIII. Additional Examples Illustrating the Use of Goodman and Kruskal's Gamma

Examples 32.2 and 32.3 are two additional examples that can be evaluated with **Goodman and Kruskal's gamma**. Since Examples 32.2 and 32.3 employ the same data as Example 32.1, they yield the same result. Example 32.4 describes the identical study described by Example 32.1, but uses a different configuration of data in order to illustrate the computation of a negative value for **gamma**.

Example 32.2 *A consumer group conducts a survey in order to determine whether a relationship exists between customer satisfaction and the price a person pays for an automobile. Each of 300 individuals who has purchased a new vehicle within the past year is classified in one of four categories based on the purchase price of one's automobile. Each subject is also classified in one of three categories with respect to how satisfied he or she is with one's automobile. The results are summarized in [Table 32.4](#). Do the data indicate there is a relationship between the price of an automobile and degree of satisfaction?*

Example 32.3 A panel of psychiatrists wants to determine whether a relationship exists between the number of years a patient is in psychotherapy and the degree of change in a patient's behavior. Each of 300 patients is categorized with respect to one of four time periods during which he or she is in psychotherapy, and one of three categories with respect to the change in behavior he or she has exhibited since initiating therapy. Specifically, the following four categories are employed with respect to psychotherapy duration: **less than one year; one to two years; more than two years to three years; more than three years**. The following three categories are employed with respect to changes in behavior: **deteriorated (–), no change, improved (+)**. Table 32.5 summarizes the data. Do the data indicate there is an association between the amount of time a patient is in psychotherapy and the degree to which he or she changes?⁶

Table 32.4 Summary of Data for Example 32.2

		Purchase price				Row sums
		Under \$10,000	\$10,000 to \$18,000	\$18,001 to \$30,000	More than \$30,000	
Level of satisfaction	Below average	70	15	10	5	100
	Average	10	60	20	10	100
	Above average	10	15	35	40	100
Column sums		90	90	65	55	300

Table 32.5 Summary of Data for Example 32.3

		Number of years in psychotherapy				Row sums
		Less than one year	One to two years	More than two years to three years	More than three years	
Amount of change	–	70	15	10	5	100
	No change	10	60	20	10	100
	+	10	15	35	40	100
Column sums		90	90	65	55	300

Example 32.4 A researcher wants to determine whether or not a relationship exists between a person's weight and birth order. Upon determining the weight and birth order of 300 subjects, each subject is categorized with respect to one of three weight categories and one of four birth order categories. Specifically, the following three categories are employed with respect to weight: **below average, average, above average**. The following four categories are employed with respect to birth order: **first born, second born, third born, fourth born and all subsequent birth orders**. Table 32.6 summarizes the data. Do the data indicate there is a significant association between a person's weight and birth order?

Table 32.6 Summary of Data for Example 32.4

		Birth order				Row sums
		1st born	2nd born	3rd born	4th born+	
Weight	Below average	5	10	15	70	100
	Average	10	20	60	10	100
	Above average	40	35	15	10	100
Column sums		55	65	90	90	300

Inspection of the data reveals that the cell frequencies in Table 32.6 are the mirror image of those employed in Table 32.1. By virtue of employing the same frequencies in an inverted format, the values of n_C and n_D for Table 32.6 are the reverse of those obtained for Table 32.1. Thus, for Table 32.6, $n_C = 3700$ and $n_D = 20875$. Consequently, employing Equation 32.1, $G = (3700 - 20875)/(3700 + 20875) = -.70$. Because the same configuration of data is employed in an inverted format, the value $G = -.70$ computed for Table 32.6 is the same absolute value computed for Table 32.1. Note that the negative correlation $G = -.70$ indicates that a subject's birth order is inversely related to his weight. Specifically, subjects in a low birth order category are more likely to be above average in weight, while subjects in a high birth order category are more likely to be below average in weight.

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Endnotes

1. The general model for an $r \times c$ contingency table (which is summarized in Table 16.1) is discussed in Section I of the **chi-square test for $r \times c$ tables (Test 16)**.
2. **Gamma** can also be computed if the ordering is reversed — i.e. within both variables, the first row/column represents the category with the highest magnitude, and the last row/column represents the category with the lowest magnitude.
3. Some sources employ the following statements as the null hypothesis and the nondirectional alternative hypothesis for **Goodman and Kruskal's gamma**: **Null hypothesis**: H_0 :

Variables X and Y are independent of one another; **Nondirectional alternative hypothesis:**
 H_1 : Variables X and Y are not independent of one another.

It is, in fact, true that if in the underlying population the two variables are independent, the value of γ will equal zero. However, Siegel and Castellan (1988) note that if $\gamma = 0$, the latter does not in and of itself ensure that the two variables are independent of one another (unless the contingency table is a 2×2 table).

4. Equation 32.2 can also be written in the following form:

$$z = (G - \gamma) \sqrt{\frac{n_C + n_D}{N(1 - G^2)}}$$

In the above equation, γ represents the value of **gamma** stated in the null hypothesis. When the latter value equals zero, the above equation reduces to Equation 32.2. When some value other than zero is stipulated for **gamma** in the null hypothesis, the equation noted above can be employed to evaluate the null hypothesis $H_0: \gamma = \gamma_0$ (where γ_0 represents the value stipulated for the population correlation).

5. Sources that discuss the evaluation of the null hypothesis $H_0: \gamma = 0$ note that the normal approximation computed with Equations 32.2/32.3 tends to be overly conservative. Consequently, the likelihood of committing a Type I error (i.e., rejecting H_0 when it is true) is actually less than the value of alpha employed in the analysis.
6. It could be argued that it might be more appropriate to employ **Somers' delta** (which is briefly discussed in Section VII) rather than **gamma** as a measure of association for Example 32.3. The use of **delta** could be justified, if within the framework of a study the number of years of therapy represents an independent variable and the amount of change represents the dependent variable. In point of fact, depending upon how one conceptualizes the relationship between the two variables, one could also argue for the use of **delta** as a measure of association for Example 32.1. In the final analysis, it will not always be clear whether it is more appropriate to employ **gamma** or **delta** as a measure of association for an ordered contingency table.

Appendix: Tables

Acknowledgments and Sources for Tables in Appendix

Table A1 Table of the Normal Distribution

Reprinted with permission of CRC Press, Boca Raton, Florida from W. H. Beyer (1968), **CRC Handbook of Tables for Probability and Statistics** (2nd ed.), Table II.1 (The normal probability function and related functions), pp. 127–134.

Table A2 Table of Student's t Distribution

Reprinted with permission from Table 12 (Percentage points for the t distribution) in E. S. Pearson and H. O. Hartley, eds. (1970), **Biometrika Tables for Statisticians** (3rd ed., Volume I). New York: Cambridge University Press. Reproduced with kind permission of **Biometrika** trustees.

Table A3 Power Curves for Student's t Distribution

Reprinted with permission of Addison–Wesley Longman Publishing Company, Inc. from Table 2.2 (Graphs of the operating characteristics of Student's t test) in D. B. Owen (©1962), **Handbook of Statistical Tables**. Reading, MA: Addison–Wesley, pp. 32–35.

Table A4 Table of the Chi-Square Distribution

Reprinted with permission from Table 8 (Percentage points of the χ^2 distribution) in E. S. Pearson and H. O. Hartley, eds. (1970), **Biometrika Tables for Statisticians** (3rd ed., Volume I). New York: Cambridge University Press. Reproduced with kind permission of **Biometrika** trustees.

Table A5 Table of Critical T Values for Wilcoxon's Signed Ranks and Matched-Pairs Signed-Ranks Tests

Material from Table II in F. Wilcoxon, S. K. Katti and R. A. Wilcox (1963), **Critical Values and Probability Levels for the Wilcoxon Rank Sum Test and the Wilcoxon Signed Rank Test**. Copyright © 1963, American Cyanamid Company, Lederle Laboratories Division. All rights reserved and reprinted with permission.

Table A6 Table of the Binomial Distribution, Individual Probabilities

Reprinted with permission of CRC Press, Boca Raton, Florida from W. H. Beyer (1968), **CRC Handbook of Tables for Probability and Statistics** (2nd ed.), Table III.1 (Individual terms, binomial distribution), pp. 182–193.

Table A7 Table of the Binomial Distribution, Cumulative Probabilities

Reprinted with permission of CRC Press, Boca Raton, Florida from W. H. Beyer (1968), **CRC Handbook of Tables for Probability and Statistics** (2nd ed.), Table III.2 (Cumulative terms, binomial distribution), pp. 194–205.

Table A8 Table of Critical Values for the Single-Sample Runs Test

Reprinted with permission of Institute of Mathematical Statistics, Hayward, CA from the following: Portions of **Table II** on pp. 83–87 from: F. S. Swed and C. Eisenhart (1943).

Tables for testing randomness of grouping in a sequence of alternatives, **Annals of Mathematical Statistics**, 14, 66–87.

Table A9 Table of the F_{\max} Distribution

Reprinted with permission from Table 31 (Percentage points of the ratio s_{\max}^2/s_{\min}^2) in E. S. Pearson and H. O. Hartley, eds. (1970). **Biometrika Tables for Statisticians** (3rd ed., Volume 1). New York: Cambridge University Press. Reproduced with the kind permission of the **Biometrika** trustees.

Table A10 Table of the F Distribution

Reprinted with permission from Table 18 (Percentage points of the F -distribution (variance ratio)) in E. S. Pearson and H. O. Hartley (eds.) (1970), **Biometrika Tables for Statisticians** (3rd ed., Volume 1). New York: Cambridge University Press. Reproduced with the kind permission of the **Biometrika** trustees. Table reproduced with permission of CRC Press, Boca Raton, Florida from W. H. Beyer (1968), **CRC Handbook of Tables for Probability and Statistics** (2nd ed.), Table VI.1 (Percentage Points, F Distribution), pp. 304–310.

Table A11 Table of Critical Values for Mann-Whitney U Statistic

Reprinted with permission of Indiana University from D. Auble (1953), Extended Tables for the Mann–Whitney Statistic. **Bulletin of the Institute of Educational Research at Indiana University** Vol. 1, No. 2. Table reproduced with permission of CRC Press, Boca Raton, Florida from W. H. Beyer (1968), **CRC Handbook of Tables for Probability and Statistics** (2nd ed.), Table X.4 (Critical Values of U in the Wilcoxon (Mann–Whitney) Two-Sample Statistic), pp. 405–408.

Table A12 Table of Sandler's A Statistic

Reprinted with permission of British Psychological Society and Joseph Sandler from J. Sandler (1955), A test of the significance of difference between the means of correlated measures based on a simplification of Student's t . **British Journal of Psychology**, 46, pp. 225–226.

Table A13 Table of the Studentized Range Statistic

Reprinted with permission from Table 29 (Percentage points of the studentized range) in E. S. Pearson and H. O. Hartley, eds. (1970), **Biometrika Tables for Statisticians** (3rd ed., Volume 1). New York: Cambridge University Press. Reproduced with the kind permission of the **Biometrika** trustees.

Table A14 Table of Dunnett's Modified t Statistic for a Control Group Comparison

Two-tailed values: Reprinted with permission of the Biometric Society, Alexandria, VA from: C. W. Dunnett (1964), New tables for multiple comparisons with a control. **Biometrics**, 20, pp. 482–491.

One-tailed values: Reprinted with permission of the American Statistical Association, Alexandria, VA from: C. W. Dunnett (1955). A multiple comparison procedure for comparing several treatments with a control. **Journal of the American Statistical Association**, 50, pp. 1096–1121.

Table A15 Graphs of the Power Function for the Analysis of Variance

Reprinted with permission of **Biometrika** from E. S. Pearson and H. O. Hartley (1951),

Charts of the power function for analysis of variance tests, derived from the non-central F distribution, **Biometrika**, 38, pp. 112–130.

Table A16 Table of Critical Values for Pearson r

Reprinted with permission from Table 13 (Percentage points for the distribution of the correlation coefficient, r , when $\rho = 0$) in E. S. Pearson and H. O. Hartley, eds. (1970), **Biometrika Tables for Statisticians** (3rd ed., Volume 1). New York: Cambridge University Press. Reproduced with the kind permission of the **Biometrika** trustees.

Table A17 Table of Fisher's z_r Transformation

Reprinted with permission from Table 14 (The z -transformation of the correlation coefficient, $z = \tanh^{-1} r$) in E. S. Pearson and H. O. Hartley, eds. (1970), **Biometrika Tables for Statisticians** (3rd ed., Volume 1). New York: Cambridge University Press. Reproduced with the kind permission of the **Biometrika** trustees.

Table A18 Table of Critical Values for Spearman's Rho

Reprinted with permission of the American Statistical Association, Alexandria, VA from: J. H. Zar (1972), Significance testing of the Spearman rank correlation coefficient. **Journal of the American Statistical Association**, 67, pp. 578–580 (Table 1, p. 579).

Table A19 Table of Critical Values for Kendall's Tau

Reprinted with permission of Blackwell Publishers and Statistica Neerlandica, from Table III in L. Kaarsemaker and A. van Wijngaarden (1953), Tables for use in rank correlation. **Statistica Neerlandica**, 7, pp. 41–54 (Copyright: The Netherlands Statistical Society (VVS)).

Table A20 Table of Critical Values for Kendall's Coefficient of Concordance

Reprinted with permission of Institute of Mathematical Statistics, Hayward, CA from: M. Friedman (1940), A comparison of alternative tests of significance for the problem of m rankings. **Annals of Mathematical Statistics**, 11, 86–92 (Table III, p. 91).

Table A21 Table of Critical Values for the Kolmogorov-Smirnov Goodness-of-Fit Test for a Single Sample

Reprinted with permission of Institute of Mathematical Statistics, Hayward, CA from: L. H. Miller (1956). Table of percentage points of Kolmogorov statistics. **Journal of the American Statistical Association**, 51, pp. 111–121.

Table A22 Table of Critical Values for the Lilliefors Test for Normality

Reprinted with permission of Institute of Mathematical Statistics, Hayward, CA from: H. W. Lilliefors (1967). On the Kolmogorov-Smirnov test for normality with mean and variance unknown. **Journal of the American Statistical Association**, 62, pp. 399–402.

Table A23 Table of Critical Values for the Kolmogorov-Smirnov Test for Two Independent Samples

Reprinted with permission of Institute of Mathematical Statistics, Hayward, CA from: F. J. Massey Jr. (1952). Distribution tables for the deviation between two sample cumulatives. **Annals of Mathematical Statistics**, 23, pp. 435–441.

Table A1 Table of the Normal Distribution

z	$p(\mu \text{ to } z)$	$p(z \text{ to tail})$	ordinate	z	$p(\mu \text{ to } z)$	$p(z \text{ to tail})$	ordinate
.00	.0000	.5000	.3989	.45	.1736	.3264	.3605
.01	.0040	.4960	.3989	.46	.1772	.3228	.3589
.02	.0080	.4920	.3989	.47	.1808	.3192	.3572
.03	.0120	.4880	.3988	.48	.1844	.3156	.3555
.04	.0160	.4840	.3986	.49	.1879	.3121	.3538
.05	.0199	.4801	.3984	.50	.1915	.3085	.3521
.06	.0239	.4761	.3982	.51	.1950	.3050	.3503
.07	.0279	.4721	.3980	.52	.1985	.3015	.3485
.08	.0319	.4681	.3977	.53	.2019	.2981	.3467
.09	.0359	.4641	.3973	.54	.2054	.2946	.3448
.10	.0398	.4602	.3970	.55	.2088	.2912	.3429
.11	.0438	.4562	.3965	.56	.2123	.2877	.3410
.12	.0478	.4522	.3961	.57	.2157	.2843	.3391
.13	.0517	.4483	.3956	.58	.2190	.2810	.3372
.14	.0557	.4443	.3951	.59	.2224	.2776	.3352
.15	.0596	.4404	.3945	.60	.2257	.2743	.3332
.16	.0636	.4364	.3939	.61	.2291	.2709	.3312
.17	.0675	.4325	.3932	.62	.2324	.2676	.3292
.18	.0714	.4286	.3925	.63	.2357	.2643	.3271
.19	.0753	.4247	.3918	.64	.2389	.2611	.3251
.20	.0793	.4207	.3910	.65	.2422	.2578	.3230
.21	.0832	.4168	.3902	.66	.2454	.2546	.3209
.22	.0871	.4129	.3894	.67	.2486	.2514	.3187
.23	.0901	.4090	.3885	.68	.2517	.2483	.3166
.24	.0948	.4052	.3876	.69	.2549	.2451	.3144
.25	.0987	.4013	.3867	.70	.2580	.2420	.3123
.26	.1026	.3974	.3857	.71	.2611	.2389	.3101
.27	.1064	.3936	.3847	.72	.2642	.2358	.3079
.28	.1103	.3897	.3836	.73	.2673	.2327	.3056
.29	.1141	.3859	.3825	.74	.2704	.2296	.3034
.30	.1179	.3821	.3814	.75	.2734	.2266	.3011
.31	.1217	.3783	.3802	.76	.2764	.2236	.2989
.32	.1255	.3745	.3790	.77	.2794	.2206	.2966
.33	.1293	.3707	.3778	.78	.2823	.2177	.2943
.34	.1331	.3669	.3765	.79	.2852	.2148	.2920
.35	.1368	.3632	.3752	.80	.2881	.2119	.2897
.36	.1406	.3594	.3739	.81	.2910	.2090	.2874
.37	.1443	.3557	.3725	.82	.2939	.2061	.2850
.38	.1480	.3520	.3712	.83	.2967	.2033	.2827
.39	.1517	.3483	.3697	.84	.2995	.2005	.2803
.40	.1554	.3446	.3683	.85	.3023	.1977	.2780
.41	.1591	.3409	.3668	.86	.3051	.1949	.2756
.42	.1628	.3372	.3653	.87	.3078	.1922	.2732
.43	.1664	.3336	.3637	.88	.3106	.1894	.2709
.44	.1700	.3300	.3621	.89	.3133	.1867	.2685

Table A1 Table of the Normal Distribution (continued)

z	$p(\mu \text{ to } z)$	$p(z \text{ to tail})$	ordinate	z	$p(\mu \text{ to } z)$	$p(z \text{ to tail})$	ordinate
.90	.3159	.1841	.2661	1.35	.4115	.0885	.1604
.91	.3186	.1814	.2637	1.36	.4131	.0869	.1582
.92	.3212	.1788	.2613	1.37	.4147	.0853	.1561
.93	.3238	.1762	.2589	1.38	.4162	.0838	.1539
.94	.3264	.1736	.2565	1.39	.4177	.0823	.1518
.95	.3289	.1711	.2541	1.40	.4192	.0808	.1497
.96	.3315	.1685	.2516	1.41	.4207	.0793	.1476
.97	.3340	.1660	.2492	1.42	.4222	.0778	.1456
.98	.3365	.1635	.2468	1.43	.4236	.0764	.1435
.99	.3389	.1611	.2444	1.44	.4251	.0749	.1415
1.00	.3413	.1587	.2420	1.45	.4265	.0735	.1394
1.01	.3438	.1562	.2396	1.46	.4279	.0721	.1374
1.02	.3461	.1539	.2371	1.47	.4292	.0708	.1354
1.03	.3485	.1515	.2347	1.48	.4306	.0694	.1334
1.04	.3508	.1492	.2323	1.49	.4319	.0681	.1315
1.05	.3531	.1469	.2299	1.50	.4332	.0668	.1295
1.06	.3554	.1446	.2275	1.51	.4345	.0655	.1276
1.07	.3577	.1423	.2251	1.52	.4357	.0643	.1257
1.08	.3599	.1401	.2227	1.53	.4370	.0630	.1238
1.09	.3621	.1379	.2203	1.54	.4382	.0618	.1219
1.10	.3643	.1357	.2179	1.55	.4394	.0606	.1200
1.11	.3665	.1335	.2155	1.56	.4406	.0594	.1182
1.12	.3686	.1314	.2131	1.57	.4418	.0582	.1163
1.13	.3708	.1292	.2107	1.58	.4429	.0571	.1145
1.14	.3729	.1271	.2083	1.59	.4441	.0559	.1127
1.15	.3749	.1251	.2059	1.60	.4452	.0548	.1109
1.16	.3770	.1230	.2036	1.61	.4463	.0537	.1092
1.17	.3790	.1210	.2012	1.62	.4474	.0526	.1074
1.18	.3810	.1190	.1989	1.63	.4484	.0516	.1057
1.19	.3830	.1170	.1965	1.64	.4495	.0505	.1040
1.20	.3849	.1151	.1942	1.65	.4505	.0495	.1023
1.21	.3869	.1131	.1919	1.66	.4515	.0485	.1006
1.22	.3888	.1112	.1895	1.67	.4525	.0475	.0989
1.23	.3907	.1093	.1872	1.68	.4535	.0465	.0973
1.24	.3925	.1075	.1849	1.69	.4545	.0455	.0957
1.25	.3944	.1056	.1826	1.70	.4554	.0446	.0940
1.26	.3962	.1038	.1804	1.71	.4564	.0436	.0925
1.27	.3980	.1020	.1781	1.72	.4573	.0427	.0909
1.28	.3997	.1003	.1758	1.73	.4582	.0418	.0893
1.29	.4015	.0985	.1736	1.74	.4591	.0409	.0878
1.30	.4032	.0968	.1714	1.75	.4599	.0401	.0863
1.31	.4049	.0951	.1691	1.76	.4608	.0392	.0848
1.32	.4066	.0934	.1669	1.77	.4616	.0384	.0833
1.33	.4082	.0918	.1447	1.78	.4625	.0375	.0818
1.34	.4099	.0901	.1626	1.79	.4633	.0367	.0804

Table A1 Table of the Normal Distribution (continued)

z	$p(\mu \text{ to } z)$	$p(z \text{ to tail})$	ordinate		z	$p(\mu \text{ to } z)$	$p(z \text{ to tail})$	ordinate
1.80	.4641	.0359	.0790		2.25	.4878	.0122	.0317
1.81	.4649	.0351	.0775		2.26	.4881	.0119	.0310
1.82	.4656	.0344	.0761		2.27	.4884	.0116	.0303
1.83	.4664	.0336	.0748		2.28	.4887	.0113	.0297
1.84	.4671	.0329	.0734		2.29	.4890	.0110	.0290
1.85	.4678	.0322	.0721		2.30	.4893	.0107	.0283
1.86	.4686	.0314	.0707		2.31	.4896	.0104	.0277
1.87	.4693	.0307	.0694		2.32	.4898	.0102	.0270
1.88	.4699	.0301	.0681		2.33	.4901	.0099	.0264
1.89	.4706	.0294	.0669		2.34	.4904	.0096	.0258
1.90	.4713	.0287	.0656		2.35	.4906	.0094	.0252
1.91	.4719	.0281	.0644		2.36	.4909	.0091	.0246
1.92	.4726	.0274	.0632		2.37	.4911	.0089	.0241
1.93	.4732	.0268	.0620		2.38	.4913	.0087	.0235
1.94	.4738	.0262	.0608		2.39	.4916	.0084	.0229
1.95	.4744	.0256	.0596		2.40	.4918	.0082	.0224
1.96	.4750	.0250	.0584		2.41	.4920	.0080	.0219
1.97	.4756	.0244	.0573		2.42	.4922	.0078	.0213
1.98	.4761	.0239	.0562		2.43	.4925	.0075	.0208
1.99	.4767	.0233	.0551		2.44	.4927	.0073	.0203
2.00	.4772	.0228	.0540		2.45	.4929	.0071	.0198
2.01	.4778	.0222	.0529		2.46	.4931	.0069	.0194
2.02	.4783	.0217	.0519		2.47	.4932	.0068	.0189
2.03	.4788	.0212	.0508		2.48	.4934	.0066	.0184
2.04	.4793	.0207	.0498		2.49	.4936	.0064	.0180
2.05	.4798	.0202	.0488		2.50	.4938	.0062	.0175
2.06	.4803	.0197	.0478		2.51	.4940	.0060	.0171
2.07	.4808	.0192	.0468		2.52	.4941	.0059	.0167
2.08	.4812	.0188	.0459		2.53	.4943	.0057	.0163
2.09	.4817	.0183	.0449		2.54	.4945	.0055	.0158
2.10	.4821	.0179	.0440		2.55	.4946	.0054	.0155
2.11	.4826	.0174	.0431		2.56	.4948	.0052	.0151
2.12	.4830	.0170	.0422		2.57	.4949	.0051	.0147
2.13	.4834	.0166	.0413		2.58	.4951	.0049	.0143
2.14	.4838	.0162	.0404		2.59	.4952	.0048	.0139
2.15	.4842	.0158	.0396		2.60	.4953	.0047	.0136
2.16	.4846	.0154	.0387		2.61	.4955	.0045	.0132
2.17	.4850	.0150	.0379		2.62	.4956	.0044	.0129
2.18	.4854	.0146	.0371		2.63	.4957	.0043	.0126
2.19	.4857	.0143	.0363		2.64	.4959	.0041	.0122
2.20	.4861	.0139	.0355		2.65	.4960	.0040	.0119
2.21	.4864	.0136	.0347		2.66	.4961	.0039	.0116
2.22	.4868	.0132	.0339		2.67	.4962	.0038	.0113
2.23	.4871	.0129	.0332		2.68	.4963	.0037	.0110
2.24	.4875	.0125	.0325		2.69	.4964	.0036	.0107

Table A1 Table of the Normal Distribution (continued)

z	$p(\mu \text{ to } z)$	$p(z \text{ to tail})$	ordinate	z	$p(\mu \text{ to } z)$	$p(z \text{ to tail})$	ordinate
2.70	.4965	.0035	.0104	3.15	.4992	.0008	.0028
2.71	.4966	.0034	.0101	3.16	.4992	.0008	.0027
2.72	.4967	.0033	.0099	3.17	.4992	.0008	.0026
2.73	.4968	.0032	.0096	3.18	.4993	.0007	.0025
2.74	.4969	.0031	.0093	3.19	.4993	.0007	.0025
2.75	.4970	.0030	.0091	3.20	.4993	.0007	.0024
2.76	.4971	.0029	.0088	3.21	.4993	.0007	.0023
2.77	.4972	.0028	.0086	3.22	.4994	.0006	.0022
2.78	.4973	.0027	.0084	3.23	.4994	.0006	.0022
2.79	.4974	.0026	.0081	3.24	.4994	.0006	.0021
2.80	.4974	.0026	.0079	3.25	.4994	.0006	.0020
2.81	.4975	.0025	.0077	3.26	.4994	.0006	.0020
2.82	.4976	.0024	.0075	3.27	.4995	.0005	.0019
2.83	.4977	.0023	.0073	3.28	.4995	.0005	.0018
2.84	.4977	.0023	.0071	3.29	.4995	.0005	.0018
2.85	.4978	.0022	.0069	3.30	.4995	.0005	.0017
2.86	.4979	.0021	.0067	3.31	.4995	.0005	.0017
2.87	.4979	.0021	.0065	3.32	.4995	.0005	.0016
2.88	.4980	.0020	.0063	3.33	.4996	.0004	.0016
2.89	.4981	.0019	.0061	3.34	.4996	.0004	.0015
2.90	.4981	.0019	.0060	3.35	.4996	.0004	.0015
2.91	.4982	.0018	.0058	3.36	.4996	.0004	.0014
2.92	.4982	.0018	.0056	3.37	.4996	.0004	.0014
2.93	.4983	.0017	.0055	3.38	.4996	.0004	.0013
2.94	.4984	.0016	.0053	3.39	.4997	.0003	.0013
2.95	.4984	.0016	.0051	3.40	.4997	.0003	.0012
2.96	.4985	.0015	.0050	3.41	.4997	.0003	.0012
2.97	.4985	.0015	.0048	3.42	.4997	.0003	.0012
2.98	.4986	.0014	.0047	3.43	.4997	.0003	.0011
2.99	.4986	.0014	.0046	3.44	.4997	.0003	.0011
3.00	.4987	.0013	.0044	3.45	.4997	.0003	.0010
3.01	.4987	.0013	.0043	3.46	.4997	.0003	.0010
3.02	.4987	.0013	.0042	3.47	.4997	.0003	.0010
3.03	.4988	.0012	.0040	3.48	.4997	.0003	.0009
3.04	.4988	.0012	.0039	3.49	.4998	.0002	.0009
3.05	.4989	.0011	.0038	3.50	.4998	.0002	.0009
3.06	.4989	.0011	.0037	3.51	.4998	.0002	.0008
3.07	.4989	.0011	.0036	3.52	.4998	.0002	.0008
3.08	.4990	.0010	.0035	3.53	.4998	.0002	.0008
3.09	.4990	.0010	.0034	3.54	.4998	.0002	.0008
3.10	.4990	.0010	.0033	3.55	.4998	.0002	.0007
3.11	.4991	.0009	.0032	3.56	.4998	.0002	.0007
3.12	.4991	.0009	.0031	3.57	.4998	.0002	.0007
3.13	.4991	.0009	.0030	3.58	.4998	.0002	.0007
3.14	.4992	.0008	.0029	3.59	.4998	.0002	.0006

Table A1 Table of the Normal Distribution (continued)

z	$p(\mu \text{ to } z)$	$p(z \text{ to tail})$	ordinate
3.60	.4998	.0002	.0006
3.61	.4998	.0002	.0006
3.62	.4999	.0001	.0006
3.63	.4999	.0001	.0005
3.64	.4999	.0001	.0005
3.65	.4999	.0001	.0005
3.66	.4999	.0001	.0005
3.67	.4999	.0001	.0005
3.68	.4999	.0001	.0005
3.69	.4999	.0001	.0004
3.70	.4999	.0001	.0004
3.71	.4999	.0001	.0004
3.72	.4999	.0001	.0004
3.73	.4999	.0001	.0004
3.74	.4999	.0001	.0004
3.75	.4999	.0001	.0004
3.76	.4999	.0001	.0003
3.77	.4999	.0001	.0003
3.78	.4999	.0001	.0003
3.79	.4999	.0001	.0003

z	$p(\mu \text{ to } z)$	$p(z \text{ to tail})$	ordinate
3.80	.4999	.0001	.0003
3.81	.4999	.0001	.0003
3.82	.4999	.0001	.0003
3.83	.4999	.0001	.0003
3.84	.4999	.0001	.0003
3.85	.4999	.0001	.0002
3.86	.4999	.0001	.0002
3.87	.4999	.0001	.0002
3.88	.4999	.0001	.0002
3.89	1.0000	.0000	.0002
3.90	1.0000	.0000	.0002
3.91	1.0000	.0000	.0002
3.92	1.0000	.0000	.0002
3.93	1.0000	.0000	.0002
3.94	1.0000	.0000	.0002
3.95	1.0000	.0000	.0002
3.96	1.0000	.0000	.0002
3.97	1.0000	.0000	.0002
3.98	1.0000	.0000	.0001
3.99	1.0000	.0000	.0001
4.00	1.0000	.0000	.0001

Table A2 Table of Student's t Distribution

Two-tailed One-tailed		.80	.50	.20	.10	.05	.02	.01	.001
		.40	.25	.10	.05	.025	.01	.005	.0005
<i>df</i>	<i>p</i>	.60	.75	.90	.95	.975	.99	.995	.9995
1		.325	1.000	3.078	6.314	12.706	31.821	63.657	636.619
2		.289	.816	1.886	2.920	4.303	6.965	9.925	31.598
3		.277	.765	1.638	2.353	3.182	4.541	5.841	12.924
4		.271	.741	1.533	2.132	2.776	3.747	4.604	8.610
5		.267	.727	1.476	2.015	2.571	3.365	4.032	6.869
6		.265	.718	1.440	1.943	2.447	3.143	3.707	5.959
7		.263	.711	1.415	1.895	2.365	2.998	3.499	5.408
8		.262	.706	1.397	1.860	2.306	2.896	3.355	5.041
9		.261	.703	1.383	1.833	2.262	2.821	3.250	4.781
10		.260	.700	1.372	1.812	2.228	2.764	3.169	4.587
11		.260	.697	1.363	1.796	2.201	2.718	3.106	4.437
12		.259	.695	1.356	1.782	2.179	2.681	3.055	4.318
13		.259	.694	1.350	1.771	2.160	2.650	3.012	4.221
14		.258	.692	1.345	1.761	2.145	2.624	2.977	4.140
15		.258	.691	1.341	1.753	2.131	2.602	2.947	4.073
16		.258	.690	1.337	1.746	2.120	2.583	2.921	4.015
17		.257	.689	1.333	1.740	2.110	2.567	2.898	3.965
18		.257	.688	1.330	1.734	2.101	2.552	2.878	3.922
19		.257	.688	1.328	1.729	2.093	2.539	2.861	3.883
20		.257	.687	1.325	1.725	2.086	2.528	2.845	3.850
21		.257	.686	1.323	1.721	2.080	2.518	2.831	3.819
22		.256	.686	1.321	1.717	2.074	2.508	2.819	3.792
23		.256	.685	1.319	1.714	2.069	2.500	2.807	3.767
24		.256	.685	1.318	1.711	2.064	2.492	2.797	3.745
25		.256	.684	1.316	1.708	2.060	2.485	2.787	3.725
26		.256	.684	1.315	1.706	2.056	2.479	2.779	3.707
27		.256	.684	1.314	1.703	2.052	2.473	2.771	3.690
28		.256	.683	1.313	1.701	2.048	2.467	2.763	3.674
29		.256	.683	1.311	1.699	2.045	2.462	2.756	3.659
30		.256	.683	1.310	1.697	2.042	2.457	2.750	3.646
40		.255	.681	1.303	1.684	2.021	2.423	2.704	3.551
60		.254	.679	1.296	1.671	2.000	2.390	2.660	3.460
120		.254	.677	1.289	1.658	1.980	2.358	2.617	3.373
∞		.253	.674	1.282	1.645	1.960	2.326	2.576	3.291

Table A3 Power Curves for Student's *t* Distribution

Table A3-A (Two-Tailed .01 and One-Tailed .005 Values)

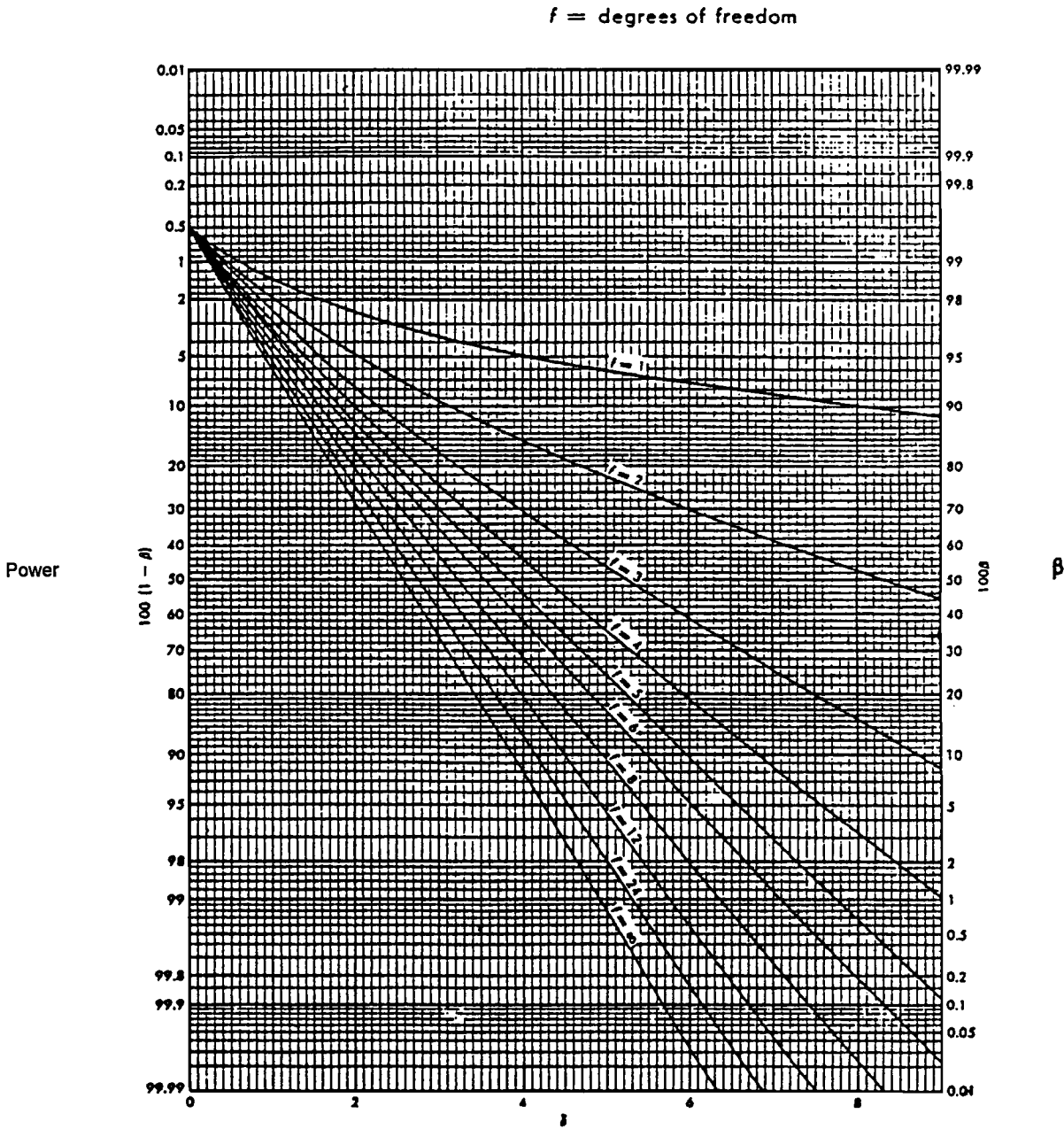


Table A3 Power Curves for Student's *t* Distribution (continued)

Table A3-B (Two-Tailed .02 and One-Tailed .01 Values)

f = degrees of freedom

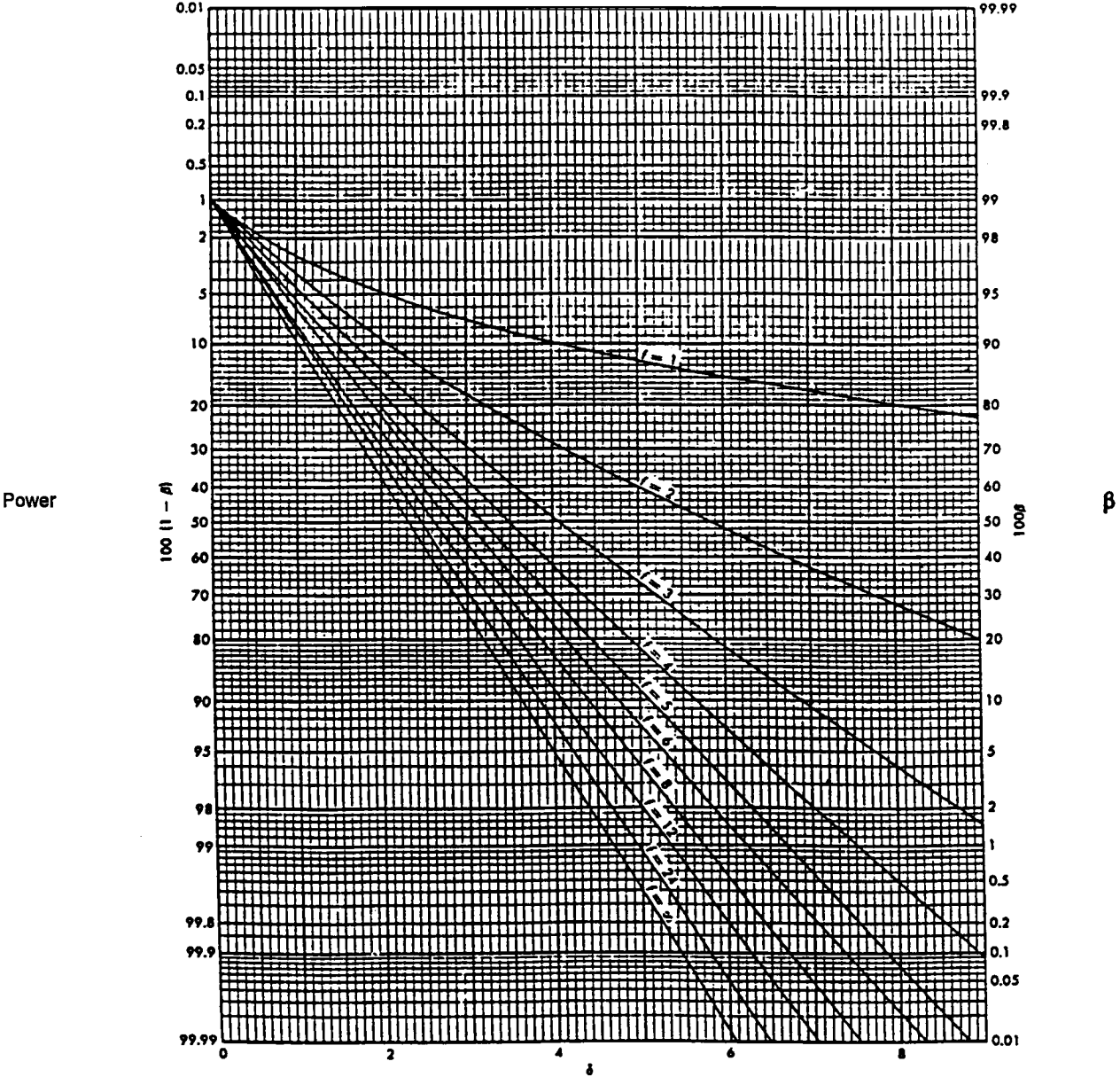


Table A3 Power Curves for Student's *t* Distribution (continued)

Table A3-C (Two-Tailed .05 and One-Tailed .025 Values)

f = degrees of freedom

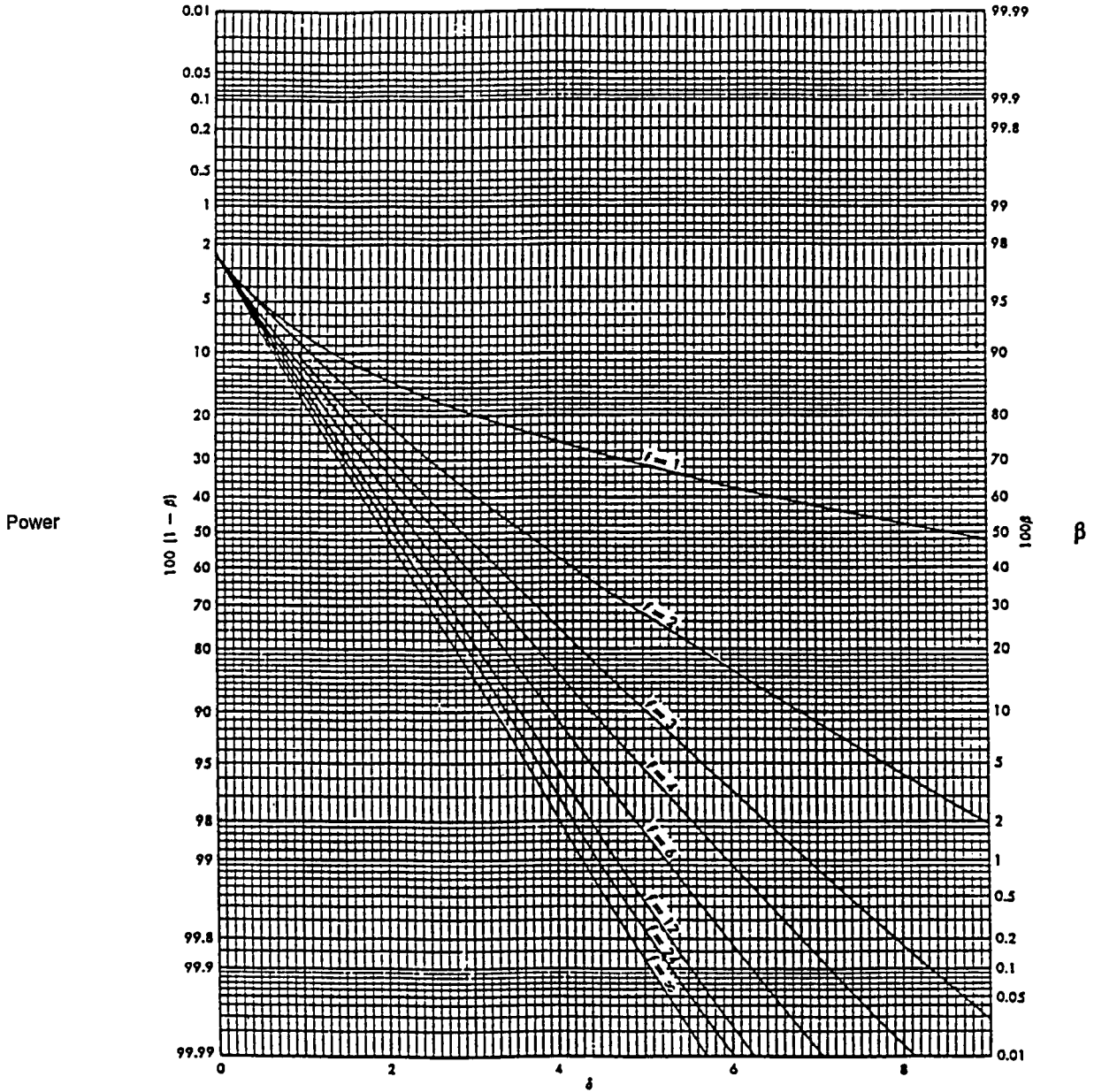


Table A3 Power Curves for Student's *t* Distribution (continued)

Table A3-D (Two-Tailed .10 and One-Tailed .05 Values)

f = degrees of freedom

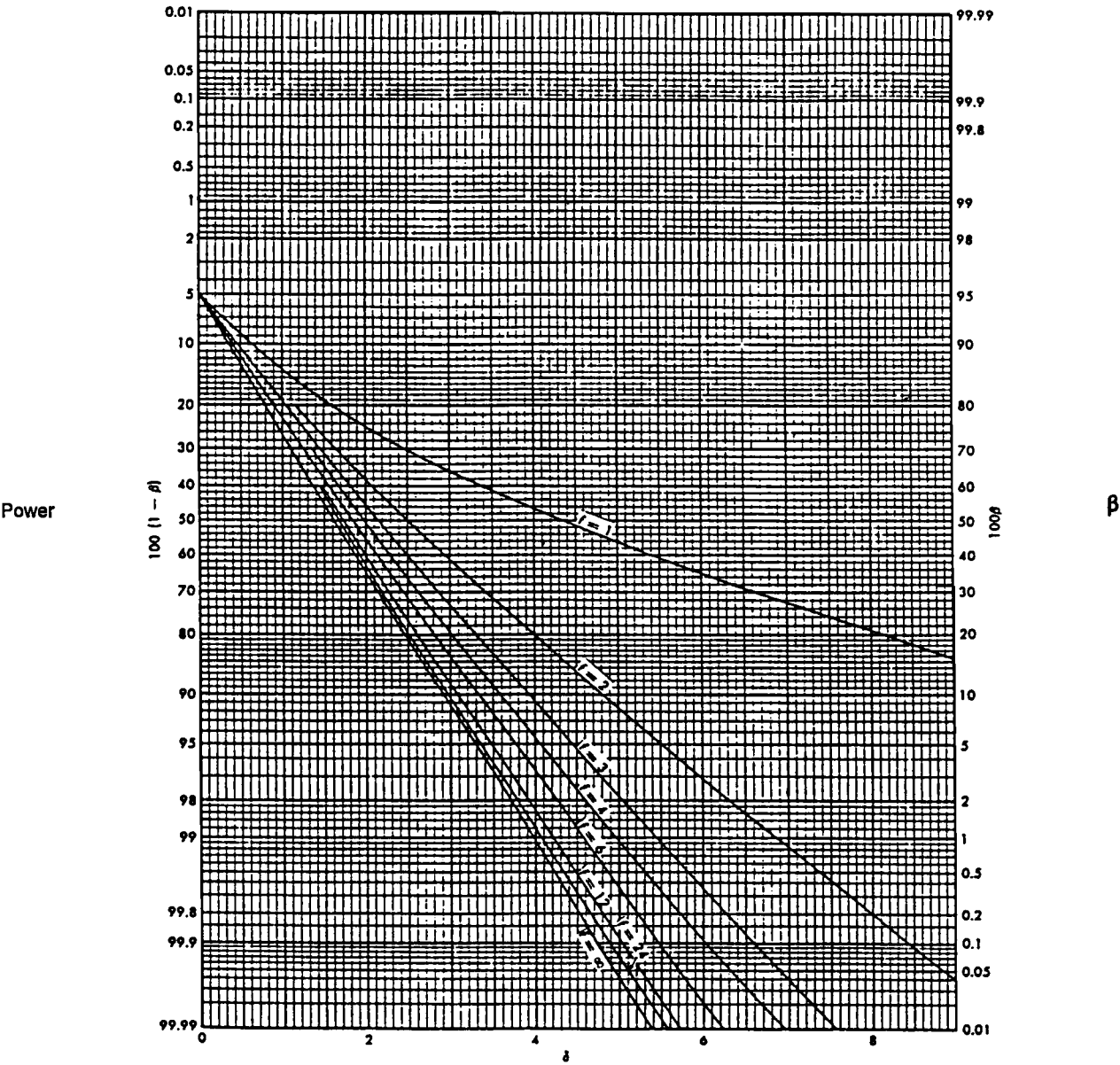


Table A4 Table of the Chi-Square Distribution

<i>p</i>	.005	.010	.025	.050	.100	.900	.950	.975	.990	.995	.999
<i>df</i>											
1	.0393	.0157	.0982	.0393	.0158	2.71	3.84	5.02	6.63	7.88	10.83
2	.0100	.0201	.0506	.103	.211	4.61	5.99	7.38	9.21	10.60	13.82
3	.072	.115	.216	.352	.584	6.25	7.81	9.35	11.34	12.84	16.27
4	.0207	.297	.484	.711	1.064	7.78	9.49	11.14	13.28	14.86	18.47
5	.412	.554	.831	1.145	1.61	9.24	11.07	12.83	15.09	16.75	20.52
6	.676	.872	1.24	1.64	2.20	10.64	12.59	14.45	16.81	18.55	22.46
7	.989	1.24	1.69	2.17	2.83	12.02	14.07	16.01	18.48	20.28	24.32
8	1.34	1.65	2.18	2.73	3.49	13.36	15.51	17.53	20.09	21.96	26.13
9	1.73	2.09	2.70	3.33	4.17	14.68	16.92	19.02	21.67	23.59	27.88
10	2.16	2.56	3.25	3.94	4.87	15.99	18.31	20.48	23.21	25.19	29.59
11	2.60	3.05	3.82	4.57	5.58	17.28	19.68	21.92	24.72	26.76	31.26
12	3.07	3.57	4.40	5.23	6.30	18.55	21.03	23.34	26.22	28.30	32.91
13	3.57	4.11	5.01	5.89	7.04	19.81	22.36	24.74	27.69	29.82	34.53
14	4.07	4.66	5.63	6.57	7.79	21.06	23.68	26.12	29.14	31.32	36.12
15	4.60	5.23	6.26	7.26	8.55	22.31	25.00	27.49	30.58	32.80	37.70
16	5.14	5.81	6.91	7.96	9.31	23.54	26.30	28.85	32.00	34.27	39.25
17	5.70	6.41	7.56	8.67	10.09	24.77	27.59	30.19	33.41	35.72	40.79
18	6.26	7.01	8.23	9.39	10.86	25.99	28.87	31.53	34.81	37.16	42.31
19	6.84	7.63	8.91	10.12	11.65	27.20	30.14	32.85	36.19	38.58	43.82
20	7.43	8.26	8.59	10.85	12.44	28.41	31.41	34.17	37.57	40.00	43.32
21	8.03	8.90	10.28	11.59	13.24	29.62	32.67	35.48	38.93	41.40	46.80
22	8.64	9.54	10.98	12.34	14.04	30.81	33.92	36.78	40.29	42.80	48.27
23	9.26	10.20	11.69	13.09	14.85	32.01	35.17	38.08	41.64	44.18	49.73
24	9.89	10.86	12.40	13.85	15.66	33.20	36.42	39.36	42.98	45.56	51.18
25	10.52	11.52	13.12	14.61	16.47	34.38	37.65	40.65	44.31	46.93	52.62
26	11.16	12.20	13.84	15.38	17.29	35.56	38.89	41.92	45.64	48.29	54.05
27	11.81	12.88	14.57	16.15	18.11	36.74	40.11	43.19	46.96	49.64	55.48
28	12.46	13.56	15.31	16.93	18.94	37.92	41.34	44.46	48.28	50.99	56.89
29	13.21	14.26	16.05	17.71	19.77	39.09	42.56	45.72	49.59	52.34	58.30
30	13.79	14.95	16.79	18.49	20.60	40.26	43.77	46.98	50.89	53.67	59.70
40	20.71	22.16	24.43	26.51	29.05	51.80	55.76	59.34	63.69	66.77	73.40
50	27.99	29.71	32.36	34.76	37.69	63.17	67.50	71.42	76.15	79.49	86.66
60	35.53	37.48	40.48	43.19	46.46	74.40	79.08	83.30	88.38	91.95	99.61
70	43.28	45.44	48.76	51.74	55.33	85.53	90.53	95.02	100.43	104.22	112.32
80	51.17	53.54	57.15	60.39	64.28	96.58	101.88	106.63	112.33	116.32	124.84
90	59.20	61.75	65.65	69.13	73.29	107.56	113.15	118.14	124.12	128.30	137.21
100	67.33	70.06	74.22	77.93	82.36	118.50	124.34	129.56	135.81	140.17	149.45

**Table A5 Table of Critical T Values for Wilcoxon's Signed-Ranks
and Matched-Pairs Signed-Ranks Test**

One-tailed level of significance					One-tailed level of significance				
.05 .025 .01 .005					.05 .025 .01 .005				
Two-tailed level of significance					Two-tailed level of significance				
.10 .05 .02 .01					.10 .05 .02 .01				
<i>n</i>					<i>n</i>				
5	0	–	–	–	28	130	116	101	91
6	2	0	–	–	29	140	126	110	100
7	3	2	0	–	30	151	137	120	109
8	5	3	1	0	31	163	147	130	118
9	8	5	3	1	32	175	159	140	128
10	10	8	5	3	33	187	170	151	138
11	13	10	7	5	34	200	182	162	148
12	17	13	9	7	35	213	195	173	159
13	21	17	12	9	36	227	208	185	171
14	25	21	15	12	37	241	221	198	182
15	30	25	19	15	38	256	235	211	194
16	35	29	23	19	39	271	249	224	207
17	41	34	27	23	40	286	264	238	220
18	47	40	32	27	41	302	279	252	233
19	53	46	37	32	42	319	294	266	247
20	60	52	43	37	43	336	310	281	261
21	67	58	49	42	44	353	327	296	276
22	75	65	55	48	45	371	343	312	291
23	83	73	62	54	46	389	361	328	307
24	91	81	69	61	47	407	378	345	322
25	100	89	76	68	48	426	396	362	339
26	110	98	84	75	49	446	415	379	355
27	119	107	92	83	50	466	434	397	373

Table A6 Table of the Binomial Distribution, Individual Probabilities

n	x	.05	.10	.15	.20	π .25	.30	.35	.40	.45	.50
1	0	.9500	.9000	.8500	.8000	.7500	.7000	.6500	.6000	.5500	.5000
	1	.0500	.1000	.1500	.2000	.2500	.3000	.3500	.4000	.4500	.5000
2	0	.9025	.8100	.7225	.6400	.5625	.4900	.4225	.3600	.3025	.2500
	1	.0950	.1800	.2550	.3200	.3750	.4200	.4550	.4800	.4950	.5000
	2	.0025	.0100	.0225	.0400	.0825	.0900	.1225	.1600	.2025	.2500
3	0	.8574	.7290	.6141	.5120	.4219	.3430	.2746	.2160	.1664	.1250
	1	.1354	.2430	.3251	.3840	.4219	.4410	.4436	.4320	.4084	.3750
	2	.0071	.0270	.0574	.0960	.1406	.1890	.2389	.2880	.3341	.3750
	3	.0001	.0010	.0034	.0080	.0156	.0270	.0429	.0640	.0911	.1250
4	0	.8145	.6561	.5220	.4096	.3164	.2401	.1785	.1296	.0915	.0625
	1	.1715	.2916	.3685	.4096	.4219	.4116	.3845	.3456	.2995	.2500
	2	.0135	.0486	.0975	.1536	.2109	.2646	.3105	.3456	.3675	.3750
	3	.0005	.0036	.0115	.0256	.0469	.0756	.1115	.1536	.2005	.2500
	4	.0000	.0001	.0005	.0016	.0039	.0081	.0150	.0256	.0410	.0625
5	0	.7738	.5905	.4437	.3277	.2373	.1681	.1160	.0778	.0503	.0312
	1	.2036	.3280	.3915	.4096	.3955	.3602	.3124	.2592	.2059	.1562
	2	.0214	.0729	.1382	.2048	.2637	.3087	.3364	.3456	.3369	.3125
	3	.0011	.0081	.0244	.0512	.0879	.1323	.1811	.2304	.2757	.3125
	4	.0000	.0004	.0022	.0064	.0146	.0284	.0488	.0768	.1128	.1562
	5	.0000	.0000	.0001	.0003	.0010	.0024	.0053	.0102	.0185	.0312
6	0	.7351	.5314	.3771	.2621	.1780	.1176	.0754	.0467	.0277	.0156
	1	.2321	.3543	.3993	.3932	.3560	.3025	.2437	.1866	.1359	.0938
	2	.0305	.0984	.1762	.2458	.2966	.3241	.3280	.3110	.2780	.2344
	3	.0021	.0146	.0415	.0819	.1318	.1852	.2355	.2765	.3032	.3125
	4	.0001	.0012	.0055	.0154	.0330	.0595	.0951	.1382	.1861	.2344
	5	.0000	.0001	.0004	.0015	.0044	.0102	.0205	.0369	.0609	.0938
	6	.0000	.0000	.0000	.0001	.0002	.0007	.0018	.0041	.0083	.0156
7	0	.6983	.4783	.3206	.2097	.1335	.0824	.0490	.0280	.0152	.0078
	1	.2573	.3720	.3960	.3670	.3115	.2471	.1848	.1306	.0872	.0547
	2	.0406	.1240	.2097	.2753	.3115	.3177	.2985	.2613	.2140	.1641
	3	.0036	.0230	.0617	.1147	.1730	.2269	.2679	.2903	.2918	.2734
	4	.0002	.0026	.0109	.0287	.0577	.0972	.1442	.1935	.2388	.2734
	5	.0000	.0002	.0012	.0043	.0115	.0250	.0466	.0774	.1172	.1641
	6	.0000	.0000	.0001	.0004	.0013	.0036	.0084	.0172	.0320	.0547
	7	.0000	.0000	.0000	.0000	.0001	.0002	.0006	.0016	.0037	.0078
8	0	.6634	.4305	.2725	.1678	.1001	.0576	.0319	.0168	.0084	.0039
	1	.2793	.3826	.3847	.3355	.2670	.1977	.1373	.0896	.0548	.0312
	2	.0515	.1488	.2376	.2936	.3115	.2965	.2587	.2090	.1569	.1094
	3	.0054	.0331	.0839	.1468	.2076	.2541	.2786	.2787	.2568	.2188
	4	.0004	.0046	.0185	.0459	.0865	.1361	.1875	.2322	.2627	.2734
	5	.0000	.0004	.0026	.0092	.0231	.0467	.0808	.1239	.1719	.2188
	6	.0000	.0000	.0002	.0011	.0038	.0100	.0217	.0413	.0703	.1094
	7	.0000	.0000	.0000	.0001	.0004	.0012	.0033	.0079	.0164	.0312
	8	.0000	.0000	.0000	.0000	.0000	.0001	.0002	.0007	.0017	.0039

Table A6 Table of the Binomial Distribution, Individual Probabilities (continued)

n	x	.05	.10	.15	.20	π .25	.30	.35	.40	.45	.50
9	0	.6302	.3874	.2316	.1342	.0751	.0404	.0207	.0101	.0046	.0020
	1	.2985	.3874	.3679	.3020	.2253	.1556	.1004	.0605	.0339	.0176
	2	.0629	.1722	.2597	.3020	.3003	.2668	.2162	.1612	.1110	.0703
	3	.0077	.0446	.1069	.1762	.2336	.2668	.2716	.2508	.2119	.1641
	4	.0006	.0074	.0283	.0661	.1168	.1715	.2194	.2508	.2600	.2461
	5	.0000	.0008	.0050	.0165	.0389	.0735	.1181	.1672	.2128	.2461
	6	.0000	.0001	.0006	.0028	.0087	.0210	.0424	.0743	.1160	.1641
	7	.0000	.0000	.0000	.0003	.0012	.0039	.0098	.0212	.0407	.0703
	8	.0000	.0000	.0000	.0000	.0001	.0004	.0013	.0035	.0083	.0176
	9	.0000	.0000	.0000	.0000	.0000	.0000	.0001	.0003	.0008	.0020
10	0	.5987	.3487	.1969	.1074	.0563	.0282	.0135	.0060	.0025	.0010
	1	.3151	.3874	.3474	.2684	.1877	.1211	.0725	.0403	.0207	.0098
	2	.0746	.1937	.2759	.3020	.2816	.2335	.1757	.1209	.0763	.0439
	3	.0105	.0574	.1298	.2013	.2503	.2868	.2522	.2150	.1665	.1172
	4	.0010	.0112	.0401	.0881	.1460	.2001	.2377	.2508	.2384	.2051
	5	.0001	.0015	.0085	.0264	.0584	.1029	.1536	.2007	.2340	.2461
	6	.0000	.0001	.0012	.0055	.0162	.0368	.0689	.1115	.1596	.2051
	7	.0000	.0000	.0001	.0008	.0031	.0090	.0212	.0425	.0746	.1172
	8	.0000	.0000	.0000	.0001	.0004	.0014	.0043	.0106	.0229	.0439
	9	.0000	.0000	.0000	.0000	.0000	.0001	.0005	.0016	.0042	.0098
	10	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0001	.0003	.0010
11	0	.5688	.3138	.1673	.0859	.0422	.0198	.0088	.0036	.0014	.0004
	1	.3293	.3835	.3248	.2362	.1549	.0932	.0518	.0266	.0125	.0055
	2	.0867	.2131	.2866	.2953	.2581	.1998	.1395	.0887	.0513	.0269
	3	.0137	.0710	.1517	.2215	.2581	.2568	.2254	.1774	.1259	.0806
	4	.0014	.0158	.0536	.1107	.1721	.2201	.2428	.2365	.2060	.1611
	5	.0001	.0025	.0132	.0388	.0803	.1321	.1830	.2207	.2360	.2256
	6	.0000	.0003	.0023	.0097	.0268	.0566	.0985	.1471	.1931	.2256
	7	.0000	.0000	.0003	.0017	.0064	.0173	.0379	.0701	.1128	.1611
	8	.0000	.0000	.0000	.0002	.0011	.0037	.0102	.0234	.0462	.0806
	9	.0000	.0000	.0000	.0000	.0001	.0005	.0018	.0052	.0126	.0269
	10	.0000	.0000	.0000	.0000	.0000	.0000	.0002	.0007	.0021	.0054
	11	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0002	.0005
12	0	.5404	.2824	.1422	.0687	.0317	.0138	.0057	.0022	.0008	.0002
	1	.3413	.3766	.3012	.2062	.1267	.0712	.0368	.0174	.0075	.0029
	2	.0988	.2301	.2924	.2835	.2323	.1678	.1088	.0639	.0339	.0161
	3	.0173	.0852	.1720	.2362	.2581	.2397	.1954	.1419	.0923	.0537
	4	.0021	.0213	.0683	.1329	.1936	.2311	.2367	.2128	.1700	.1208
	5	.0002	.0038	.0193	.0532	.1032	.1585	.2039	.2270	.2225	.1934
	6	.0000	.0005	.0040	.0155	.0401	.0792	.1281	.1768	.2124	.2256
	7	.0000	.0000	.0006	.0033	.0115	.0291	.0591	.1009	.1489	.1934
	8	.0000	.0000	.0001	.0005	.0024	.0078	.0199	.0420	.0762	.1208
	9	.0000	.0000	.0000	.0001	.0004	.0015	.0048	.0125	.0277	.0537
	10	.0000	.0000	.0000	.0000	.0000	.0002	.0008	.0025	.0068	.0161
	11	.0000	.0000	.0000	.0000	.0000	.0000	.0001	.0003	.0010	.0029
	12	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0001	.0002

Table A6 Table of the Binomial Distribution, Individual Probabilities (continued)

n	x	.05	.10	.15	.20	π .25	.30	.35	.40	.45	.50
13	0	.5133	.2542	.1209	.0550	.0238	.0097	.0037	.0013	.0004	.0001
	1	.3512	.3672	.2774	.1787	.1029	.0540	.0259	.0113	.0045	.0016
	2	.1109	.2448	.2937	.2680	.2059	.1388	.0836	.0453	.0220	.0095
	3	.0214	.0997	.1900	.2457	.2517	.2181	.1651	.1107	.0660	.0349
	4	.0028	.0277	.0838	.1535	.2097	.2337	.2222	.1845	.1350	.0873
	5	.0003	.0055	.0266	.0691	.1258	.1803	.2154	.2214	.1989	.1571
	6	.0000	.0008	.0063	.0230	.0559	.1030	.1548	.1968	.2169	.2095
	7	.0000	.0001	.0011	.0058	.0186	.0442	.0833	.1312	.1775	.2095
	8	.0000	.0000	.0001	.0011	.0047	.0142	.0336	.0656	.1089	.1571
	9	.0000	.0000	.0000	.0001	.0009	.0034	.0101	.0243	.0495	.0873
	10	.0000	.0000	.0000	.0000	.0001	.0006	.0022	.0065	.0162	.0349
	11	.0000	.0000	.0000	.0000	.0000	.0001	.0003	.0012	.0036	.0095
	12	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0001	.0005	.0016
	13	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0001
14	0	.4877	.2288	.1028	.0440	.0178	.0068	.0024	.0008	.0002	.0001
	1	.3593	.3559	.2539	.1539	.0832	.0407	.0181	.0073	.0027	.0009
	2	.1229	.2570	.2912	.2501	.1802	.1134	.0634	.0317	.0141	.0056
	3	.0259	.1142	.2056	.2501	.2402	.1943	.1366	.0845	.0462	.0222
	4	.0037	.0349	.0998	.1720	.2202	.2290	.2022	.1549	.1040	.0611
	5	.0004	.0078	.0352	.0860	.1488	.1963	.2178	.2066	.1701	.1222
	6	.0000	.0013	.0093	.0322	.0734	.1282	.1759	.2066	.2088	.1833
	7	.0000	.0002	.0019	.0092	.0280	.0618	.1082	.1574	.1952	.2095
	8	.0000	.0000	.0003	.0020	.0082	.0232	.0510	.0918	.1398	.1833
	9	.0000	.0000	.0000	.0003	.0018	.0066	.0183	.0408	.0762	.1222
	10	.0000	.0000	.0000	.0000	.0003	.0014	.0049	.0136	.0312	.0611
	11	.0000	.0000	.0000	.0000	.0000	.0002	.0010	.0033	.0093	.0222
	12	.0000	.0000	.0000	.0000	.0000	.0000	.0001	.0005	.0019	.0056
	13	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0001	.0002	.0009
	14	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0001
15	0	.4633	.2059	.0874	.0352	.0134	.0047	.0016	.0005	.0001	.0000
	1	.3658	.3432	.2312	.1319	.0668	.0305	.0126	.0047	.0016	.0005
	2	.1348	.2669	.2856	.2309	.1559	.0916	.0476	.0219	.0090	.0032
	3	.0307	.1285	.2184	.2501	.2252	.1700	.1110	.0634	.0318	.0139
	4	.0049	.0428	.1156	.1876	.2252	.2186	.1792	.1268	.0780	.0417
	5	.0006	.0105	.0449	.1032	.1651	.2061	.2123	.1859	.1404	.0916
	6	.0000	.0019	.0132	.0430	.0917	.1472	.1906	.2066	.1914	.1527
	7	.0000	.0003	.0030	.0138	.0393	.0811	.1319	.1771	.2013	.1964
	8	.0000	.0000	.0005	.0035	.0131	.0348	.0710	.1181	.1647	.1964
	9	.0000	.0000	.0001	.0007	.0034	.0116	.0298	.0612	.1048	.1527
	10	.0000	.0000	.0000	.0001	.0007	.0030	.0096	.0245	.0515	.0916
	11	.0000	.0000	.0000	.0000	.0001	.0006	.0024	.0074	.0191	.0417
	12	.0000	.0000	.0000	.0000	.0000	.0001	.0004	.0016	.0052	.0139
	13	.0000	.0000	.0000	.0000	.0000	.0000	.0001	.0003	.0010	.0032
	14	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0001	.0005
	15	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000

Table A7 Table of the Binomial Distribution, Cumulative Probabilities

n	x	π									
		.05	.10	.15	.20	.25	.30	.35	.40	.45	.50
2	1	.0975	.1900	.2775	.3600	.4375	.5100	.5775	.6400	.6975	.7500
	2	.0025	.0100	.0225	.0400	.0625	.0900	.1225	.1600	.2025	.2500
3	1	.1426	.2710	.3859	.4880	.5781	.6570	.7254	.7840	.8336	.8750
	2	.0072	.0280	.0608	.1040	.1562	.2160	.2818	.3520	.4252	.5000
	3	.0001	.0010	.0034	.0080	.0156	.0270	.0429	.0640	.0911	.1250
4	1	.1855	.3439	.4780	.5904	.6836	.7599	.8215	.8704	.9085	.9375
	2	.0140	.0523	.1095	.1808	.2617	.3483	.4370	.5248	.6090	.6875
	3	.0005	.0037	.0120	.0272	.0508	.0837	.1265	.1792	.2415	.3125
	4	.0000	.0001	.0005	.0016	.0039	.0081	.0150	.0256	.0410	.0625
5	1	.2262	.4095	.5563	.6723	.7627	.8319	.8840	.9222	.9497	.9688
	2	.0226	.0815	.1648	.2627	.3672	.4718	.5716	.6630	.7438	.8125
	3	.0012	.0086	.0266	.0579	.1035	.1631	.2352	.3174	.4069	.5000
	4	.0000	.0005	.0022	.0067	.0156	.0308	.0540	.0870	.1312	.1875
	5	.0000	.0000	.0001	.0003	.0010	.0024	.0053	.0102	.0185	.0312
6	1	.2649	.4686	.6229	.7379	.8220	.8824	.9246	.9533	.9723	.9844
	2	.0328	.1143	.2235	.3447	.4661	.5798	.6809	.7667	.8364	.8906
	3	.0022	.0158	.0473	.0989	.1694	.2557	.3529	.4557	.5585	.6562
	4	.0001	.0013	.0059	.0170	.0376	.0705	.1174	.1792	.2553	.3438
	5	.0000	.0001	.0004	.0016	.0046	.0109	.0223	.0410	.0692	.1094
	6	.0000	.0000	.0000	.0001	.0002	.0007	.0018	.0041	.0083	.0156
7	1	.3017	.5217	.6794	.7903	.8665	.9176	.9510	.9720	.9848	.9922
	2	.0444	.1497	.2834	.4233	.5551	.6706	.7662	.8414	.8976	.9375
	3	.0038	.0257	.0738	.1480	.2436	.3529	.4677	.5801	.6836	.7734
	4	.0002	.0027	.0121	.0333	.0706	.1260	.1998	.2898	.3917	.5000
	5	.0000	.0002	.0012	.0047	.0129	.0288	.0556	.0963	.1529	.2266
	6	.0000	.0000	.0001	.0004	.0013	.0038	.0090	.0188	.0357	.0625
	7	.0000	.0000	.0000	.0000	.0001	.0002	.0006	.0016	.0037	.0078
8	1	.3386	.5695	.7275	.8322	.8999	.9424	.9681	.9832	.9916	.9961
	2	.0572	.1869	.3428	.4967	.6329	.7447	.8309	.8936	.9368	.9648
	3	.0058	.0381	.1052	.2031	.3215	.4482	.5722	.6846	.7799	.8555
	4	.0004	.0050	.0214	.0563	.1138	.1941	.2936	.4059	.5230	.6367
	5	.0000	.0004	.0029	.0104	.0273	.0580	.1061	.1737	.2604	.3633
	6	.0000	.0000	.0002	.0012	.0042	.0113	.0253	.0498	.0885	.1445
	7	.0000	.0000	.0000	.0001	.0004	.0013	.0036	.0085	.0181	.0352
	8	.0000	.0000	.0000	.0000	.0000	.0001	.0002	.0007	.0017	.0039
9	1	.3698	.6126	.7684	.8658	.9249	.9596	.9793	.9899	.9954	.9980
	2	.0712	.2252	.4005	.5638	.6997	.8040	.8789	.9295	.9615	.9805
	3	.0084	.0530	.1409	.2618	.3993	.5372	.6627	.7682	.8505	.9102
	4	.0006	.0083	.0339	.0856	.1657	.2703	.3911	.5174	.6386	.7461
	5	.0000	.0009	.0066	.0196	.0489	.0988	.1717	.2666	.3786	.5000
	6	.0000	.0001	.0006	.0031	.0100	.0253	.0536	.0994	.1658	.2539
	7	.0000	.0000	.0000	.0003	.0013	.0043	.0112	.0250	.0498	.0898
	8	.0000	.0000	.0000	.0000	.0001	.0004	.0014	.0038	.0091	.0195
	9	.0000	.0000	.0000	.0000	.0000	.0000	.0001	.0003	.0008	.0020

Table A7 Table of the Binomial Distribution, Cumulative Probabilities (continued)

n	z	.05	.10	.15	.20	π .25	.30	.35	.40	.45	.50
10	1	.4013	.6513	.8031	.8928	.9437	.9718	.9865	.9940	.9975	.9990
	2	.0861	.2639	.4557	.6242	.7560	.8507	.9140	.9536	.9767	.9893
	3	.0115	.0702	.1798	.3222	.4744	.6172	.7384	.8327	.9004	.9453
	4	.0010	.0128	.0500	.1209	.2241	.3504	.4862	.6177	.7340	.8281
	5	.0001	.0016	.0099	.0328	.0781	.1503	.2485	.3669	.4956	.6230
	6	.0000	.0001	.0014	.0064	.0197	.0473	.0949	.1662	.2616	.3770
	7	.0000	.0000	.0001	.0009	.0035	.0106	.0260	.0548	.1020	.1719
	8	.0000	.0000	.0000	.0001	.0004	.0016	.0048	.0123	.0274	.0547
	9	.0000	.0000	.0000	.0000	.0000	.0001	.0005	.0017	.0045	.0107
	10	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0001	.0003	.0010
11	1	.4312	.6862	.8327	.9141	.9578	.9802	.9912	.9964	.9986	.9995
	2	.1019	.3026	.5078	.6779	.8029	.8870	.9394	.9698	.9861	.9941
	3	.0152	.0896	.2212	.3826	.5448	.6873	.7999	.8811	.9348	.9673
	4	.0016	.0185	.0694	.1611	.2867	.4304	.5744	.7037	.8089	.8867
	5	.0001	.0028	.0159	.0504	.1146	.2103	.3317	.4672	.6029	.7256
	6	.0000	.0003	.0027	.0117	.0343	.0782	.1487	.2465	.3669	.5000
	7	.0000	.0000	.0003	.0020	.0076	.0216	.0501	.0994	.1738	.2744
	8	.0000	.0000	.0000	.0002	.0012	.0043	.0122	.0293	.0610	.1133
	9	.0000	.0000	.0000	.0000	.0001	.0006	.0020	.0059	.0148	.0327
	10	.0000	.0000	.0000	.0000	.0000	.0000	.0002	.0007	.0022	.0059
12	11	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0002	.0005
	1	.4596	.7176	.8578	.9313	.9683	.9862	.9943	.9978	.9992	.9998
	2	.1184	.3410	.5565	.7251	.8416	.9150	.9576	.9804	.9917	.9968
	3	.0196	.1109	.2642	.4417	.6093	.7472	.8487	.9166	.9579	.9807
	4	.0022	.0256	.0922	.2054	.3512	.5075	.6533	.7747	.8655	.9270
	5	.0002	.0043	.0239	.0726	.1576	.2763	.4167	.5618	.6956	.8062
	6	.0000	.0005	.0046	.0194	.0544	.1178	.2127	.3348	.4731	.6128
	7	.0000	.0001	.0007	.0039	.0143	.0386	.0846	.1582	.2607	.3872
	8	.0000	.0000	.0001	.0006	.0028	.0095	.0255	.0573	.1117	.1938
	9	.0000	.0000	.0000	.0001	.0004	.0017	.0056	.0153	.0356	.0730
13	10	.0000	.0000	.0000	.0000	.0000	.0002	.0008	.0028	.0079	.0193
	11	.0000	.0000	.0000	.0000	.0000	.0000	.0001	.0003	.0011	.0032
	12	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0001	.0002
	1	.4867	.7458	.8791	.9450	.9762	.9903	.9963	.9987	.9996	.9999
	2	.1354	.3787	.6017	.7684	.8733	.9363	.9704	.9874	.9951	.9983
	3	.0245	.1339	.2704	.4983	.6674	.7975	.8868	.9421	.9731	.9888
	4	.0031	.0342	.0967	.2527	.4157	.5794	.7217	.8314	.9071	.9539
	5	.0003	.0065	.0260	.0991	.2060	.3457	.4995	.6470	.7721	.8666
	6	.0000	.0009	.0053	.0300	.0802	.1654	.2841	.4256	.5732	.7095
	7	.0000	.0001	.0013	.0070	.0243	.0624	.1295	.2288	.3563	.5000
13	8	.0000	.0000	.0002	.0012	.0056	.0182	.0462	.0977	.1788	.2905
	9	.0000	.0000	.0000	.0002	.0010	.0040	.0126	.0321	.0698	.1334
	10	.0000	.0000	.0000	.0000	.0001	.0007	.0025	.0078	.0203	.0461
	11	.0000	.0000	.0000	.0000	.0000	.0001	.0003	.0013	.0041	.0112
	12	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0001	.0005	.0017
	13	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0001

Table A7 Table of the Binomial Distribution, Cumulative Probabilities (continued)

n	x	.05	.10	.15	.20	π .25	.30	.35	.40	.45	.50
14	1	.5123	.7712	.8972	.9560	.9822	.9932	.9976	.9992	.9998	.9999
	2	.1530	.4154	.6433	.8021	.8990	.9525	.9795	.9919	.9971	.9991
	3	.0301	.1584	.3521	.5519	.7189	.8392	.9161	.9602	.9830	.9935
	4	.0042	.0441	.1465	.3018	.4787	.6448	.7795	.8757	.9368	.9713
	5	.0004	.0092	.0467	.1298	.2585	.4158	.5773	.7207	.8328	.9102
	6	.0000	.0015	.0115	.0439	.1117	.2195	.3595	.5141	.6627	.7880
	7	.0000	.0002	.0022	.0116	.0383	.0933	.1836	.3075	.4539	.6047
	8	.0000	.0000	.0003	.0024	.0103	.0315	.0753	.1501	.2586	.3953
	9	.0000	.0000	.0000	.0004	.0022	.0083	.0243	.0583	.1189	.2120
	10	.0000	.0000	.0000	.0000	.0003	.0017	.0060	.0175	.0426	.0898
	11	.0000	.0000	.0000	.0000	.0000	.0002	.0011	.0039	.0114	.0287
	12	.0000	.0000	.0000	.0000	.0000	.0000	.0001	.0006	.0022	.0065
	13	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0001	.0003	.0009
	14	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0001
15	1	.5367	.7941	.9126	.9648	.9866	.9953	.9984	.9995	.9999	1.0000
	2	.1710	.4510	.6814	.8329	.9198	.9647	.9858	.9948	.9983	.9995
	3	.0362	.1841	.3958	.6020	.7639	.8732	.9383	.9729	.9893	.9963
	4	.0055	.0556	.1773	.3518	.5387	.7031	.8273	.9095	.9576	.9824
	5	.0006	.0127	.0617	.1642	.3135	.4845	.6481	.7827	.8796	.9408
	6	.0001	.0022	.0168	.0611	.1484	.2784	.4357	.5968	.7392	.8491
	7	.0000	.0003	.0036	.0181	.0566	.1311	.2452	.3902	.5478	.6964
	8	.0000	.0000	.0006	.0042	.0173	.0500	.1132	.2131	.3465	.5000
	9	.0000	.0000	.0001	.0008	.0042	.0152	.0422	.0950	.1818	.3036
	10	.0000	.0000	.0000	.0001	.0008	.0037	.0124	.0338	.0769	.1509
	11	.0000	.0000	.0000	.0000	.0001	.0007	.0028	.0093	.0255	.0592
	12	.0000	.0000	.0000	.0000	.0000	.0001	.0005	.0019	.0063	.0176
	13	.0000	.0000	.0000	.0000	.0000	.0000	.0001	.0003	.0011	.0037
	14	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0001	.0005
	15	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000

Table A8 Table of Critical Values for the Single-Sample Runs Test

Numbers listed are tabled critical two-tailed .05 and one-tailed .025 values.

n_1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
n_2																				
2											2	2	2	2	2	2	2	2	2	
											—	—	—	—	—	—	—	—	—	
3					2	2	2	2	2	2	2	2	2	3	3	3	3	3	3	
					—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	
4				2	2	2	3	3	3	3	3	3	3	3	4	4	4	4	4	
				9	9	—	—	—	—	—	—	—	—	—	—	—	—	—	—	
5			2	2	3	3	3	3	3	4	4	4	4	4	4	4	5	5	5	
			9	10	10	11	11	—	—	—	—	—	—	—	—	—	—	—	—	
6		2	2	3	3	3	3	4	4	4	4	5	5	5	5	5	5	6	6	
		—	9	10	11	12	12	13	13	13	13	—	—	—	—	—	—	—	—	
7		2	2	3	3	3	4	4	5	5	5	5	5	6	6	6	6	6	6	
		—	—	11	12	13	13	14	14	14	14	15	15	15	—	—	—	—	—	
8		2	3	3	3	4	4	5	5	5	6	6	6	6	6	7	7	7	7	
		—	—	11	12	13	14	14	15	15	16	16	16	16	17	17	17	17	17	
9		2	3	3	4	4	5	5	5	6	6	6	7	7	7	7	8	8	8	
		—	—	—	13	14	14	15	16	16	16	17	17	18	18	18	18	18	18	
10		2	3	3	4	5	5	5	6	6	7	7	7	7	8	8	8	8	9	
		—	—	—	13	14	15	16	16	17	17	18	18	18	19	19	19	20	20	
11		2	3	4	4	5	5	6	6	7	7	7	8	8	8	9	9	9	9	
		—	—	—	13	14	15	16	17	17	18	19	19	19	20	20	20	21	21	
12	2	2	3	4	4	5	6	6	7	7	7	8	8	8	9	9	9	10	10	
	—	—	—	—	13	14	16	16	17	18	19	19	20	20	21	21	21	22	22	
13	2	2	3	4	5	5	6	6	7	7	8	8	9	9	9	10	10	10	10	
	—	—	—	—	—	15	16	17	18	19	19	20	20	21	21	22	22	23	23	
14	2	2	3	4	5	5	6	7	7	8	8	9	9	9	10	10	10	11	11	
	—	—	—	—	—	15	16	17	18	19	20	20	21	22	22	23	23	23	24	
15	2	3	3	4	5	6	6	7	7	8	8	9	9	10	10	11	11	11	12	
	—	—	—	—	—	15	16	18	18	19	20	21	22	22	23	23	24	24	25	
16	2	3	4	4	5	6	6	7	8	8	9	9	10	10	11	11	11	12	12	
	—	—	—	—	—	—	17	18	19	20	21	21	22	23	23	24	25	25	25	
17	2	3	4	4	5	6	7	7	8	9	9	10	10	11	11	11	12	12	13	
	—	—	—	—	—	—	17	18	19	20	21	22	23	23	24	25	25	26	26	
18	2	3	4	5	5	6	7	8	8	9	9	10	10	11	11	12	12	13	13	
	—	—	—	—	—	—	17	18	19	20	21	22	23	24	25	25	26	26	27	
19	2	3	4	5	6	6	7	8	8	9	10	10	11	11	12	12	13	13	13	
	—	—	—	—	—	—	17	18	20	21	22	23	23	24	25	26	26	27	27	
20	2	3	4	5	6	6	7	8	9	9	10	10	11	12	12	13	13	13	14	
	—	—	—	—	—	—	17	18	20	21	22	23	24	25	25	26	27	27	28	

Table A9 Table of the F_{\max} Distribution

The .05 critical values are in lightface type, and the .01 critical values are in **bold** type.

$n - 1$	k	2	3	4	5	6	7	8	9	10	11	12
2		39 199	87.5 448	142 729	202 1036	266 1362	333 1705	403 2063	475 2432	550 2813	626 3204	704 3605
3		15.4 47.5	27.8 85	39.2 120	50.7 151	62 184	72.9 216*	83.5 249*	93.9 281*	104 310*	114 337*	124 361*
4		9.60 23.2	15.5 37	20.6 49	25.2 59	29.5 69	33.6 79	37.5 89	41.4 97	44.6 106	48.0 113	51.4 120
5		7.15 14.9	10.8 22	13.7 28	16.3 33	18.7 38	20.8 42	22.9 46	24.7 50	26.5 54	28.2 57	29.9 60
6		5.82 11.1	8.38 15.5	10.4 19.1	12.1 22	13.7 25	15.0 27	16.3 30	17.5 32	18.6 34	19.7 36	20.7 37
7		4.99 8.89	6.94 12.1	8.44 14.5	9.70 16.5	10.8 18.4	11.8 20.	12.7 22	13.5 23	14.3 24	15.1 26	15.8 27
8		4.43 7.50	6.00 9.9	7.18 11.7	8.12 13.2	9.03 14.5	9.78 15.8	10.5 16.9	11.1 17.9	11.7 18.9	12.2 19.8	12.7 21
9		4.03 6.54	5.34 8.5	6.31 9.9	7.11 11.1	7.80 12.1	8.41 13.1	8.95 13.9	9.45 14.7	9.91 15.3	10.3 16.0	10.7 16.6
10		3.72 5.85	4.85 7.4	5.67 8.6	6.34 9.6	6.92 10.4	7.42 11.1	7.87 11.8	8.28 12.4	8.66 12.9	9.01 13.4	9.34 13.9
12		3.28 4.91	4.16 6.1	4.79 6.9	5.30 7.6	5.72 8.2	6.09 8.7	6.42 9.1	6.72 9.5	7.00 9.9	7.25 10.2	7.48 10.6
15		2.86 4.07	3.54 4.9	4.01 5.5	4.37 6.0	4.68 6.4	4.95 6.7	5.19 7.1	5.40 7.3	5.59 7.5	5.77 7.8	5.93 8.0
20		2.46 3.32	2.95 3.8	3.29 4.3	3.54 4.6	3.76 4.9	3.94 5.1	4.10 5.3	4.24 5.5	4.37 5.6	4.49 5.8	4.59 5.9
30		2.07 2.63	2.40 3.0	2.61 3.3	2.78 3.5	2.91 3.6	3.02 3.7	3.12 3.8	3.21 3.9	3.29 4.0	3.36 4.1	3.39 4.2
60		1.67 1.96	1.85 2.2	1.96 2.3	2.04 2.4	2.11 2.4	2.17 2.5	2.22 2.5	2.26 2.6	2.30 2.6	2.33 2.7	2.36 2.7

* The third digit in these values is an approximation

Table A10 Table of the F Distribution $F_{.95}$

$\frac{df_{num}}{df_{den}}$	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	161.4	198.5	215.7	224.6	230.2	234.0	236.8	238.9	240.5	241.9	243.9	245.9	248.0	249.1	250.1	251.1	252.2	253.3	254.3
2	18.51	19.00	19.16	19.25	19.30	19.33	19.35	19.37	19.38	19.40	19.41	19.43	19.45	19.45	19.46	19.47	19.48	19.49	19.50
3	10.13	9.55	9.28	9.12	9.01	8.94	8.88	8.85	8.81	8.79	8.74	8.70	8.66	8.64	8.62	8.59	8.57	8.55	8.53
4	7.71	6.94	6.69	6.39	6.26	6.16	6.09	6.04	6.00	5.96	5.91	5.86	5.80	5.77	5.75	5.72	5.69	5.66	5.63
5	6.61	5.79	5.41	5.19	5.05	4.95	4.88	4.82	4.77	4.74	4.68	4.62	4.56	4.53	4.50	4.46	4.43	4.40	4.36
6	5.99	5.14	4.76	4.53	4.39	4.28	4.21	4.15	4.10	4.06	4.00	3.94	3.87	3.84	3.81	3.77	3.74	3.70	3.67
7	5.59	4.74	4.36	4.12	3.97	3.87	3.79	3.73	3.68	3.64	3.57	3.51	3.44	3.41	3.38	3.34	3.30	3.27	3.23
8	5.32	4.46	4.07	3.84	3.69	3.58	3.50	3.44	3.39	3.35	3.28	3.22	3.15	3.12	3.08	3.04	3.01	2.97	2.93
9	5.12	4.26	3.86	3.63	3.48	3.37	3.29	3.23	3.18	3.14	3.07	3.01	2.94	2.90	2.86	2.83	2.79	2.76	2.71
10	4.90	4.10	3.71	3.48	3.33	3.22	3.14	3.07	3.02	2.98	2.91	2.85	2.77	2.74	2.70	2.66	2.62	2.58	2.54
11	4.84	3.98	3.59	3.36	3.20	3.09	3.01	2.95	2.90	2.85	2.79	2.72	2.65	2.61	2.57	2.53	2.49	2.45	2.40
12	4.75	3.89	3.49	3.26	3.11	3.00	2.91	2.85	2.80	2.75	2.69	2.62	2.54	2.51	2.47	2.43	2.38	2.34	2.30
13	4.67	3.81	3.41	3.18	3.03	2.92	2.83	2.77	2.71	2.67	2.60	2.53	2.46	2.42	2.38	2.34	2.30	2.25	2.21
14	4.60	3.74	3.34	3.11	2.96	2.85	2.76	2.70	2.65	2.60	2.53	2.46	2.39	2.35	2.31	2.27	2.22	2.18	2.13
15	4.54	3.68	3.29	3.06	2.90	2.79	2.71	2.64	2.59	2.54	2.48	2.40	2.33	2.29	2.25	2.20	2.16	2.11	2.07
16	4.49	3.63	3.24	3.01	2.85	2.74	2.66	2.59	2.54	2.49	2.42	2.35	2.28	2.24	2.19	2.15	2.11	2.06	2.01
17	4.45	3.59	3.20	2.96	2.81	2.70	2.61	2.55	2.49	2.45	2.38	2.31	2.23	2.19	2.15	2.10	2.06	2.01	1.96
18	4.41	3.55	3.16	2.93	2.77	2.66	2.58	2.51	2.46	2.41	2.34	2.27	2.19	2.15	2.11	2.06	2.02	1.97	1.92
19	4.38	3.52	3.13	2.90	2.74	2.63	2.54	2.48	2.42	2.38	2.31	2.23	2.16	2.11	2.07	2.03	1.98	1.93	1.88
20	4.35	3.49	3.10	2.87	2.71	2.60	2.51	2.45	2.39	2.35	2.28	2.20	2.12	2.08	2.04	1.99	1.95	1.90	1.84
21	4.32	3.47	3.07	2.84	2.68	2.57	2.48	2.42	2.37	2.32	2.25	2.18	2.10	2.05	2.01	1.96	1.92	1.87	1.81
22	4.30	3.44	3.05	2.82	2.66	2.55	2.46	2.40	2.34	2.30	2.23	2.15	2.07	2.03	1.98	1.94	1.89	1.84	1.78
23	4.28	3.42	3.03	2.80	2.64	2.53	2.44	2.37	2.32	2.27	2.20	2.13	2.05	2.01	1.96	1.91	1.86	1.81	1.76
24	4.26	3.40	3.01	2.78	2.62	2.51	2.42	2.36	2.30	2.25	2.18	2.11	2.03	1.98	1.94	1.89	1.84	1.79	1.73
25	4.24	3.39	2.99	2.76	2.60	2.49	2.40	2.34	2.28	2.24	2.16	2.09	2.01	1.96	1.92	1.87	1.82	1.77	1.71
26	4.23	3.37	2.98	2.74	2.59	2.47	2.39	2.32	2.27	2.22	2.15	2.07	1.99	1.95	1.90	1.85	1.80	1.75	1.69
27	4.21	3.35	2.96	2.73	2.57	2.46	2.37	2.31	2.25	2.20	2.13	2.06	1.97	1.93	1.88	1.84	1.79	1.73	1.67
28	4.20	3.34	2.95	2.71	2.56	2.45	2.36	2.29	2.24	2.19	2.12	2.04	1.96	1.91	1.87	1.82	1.77	1.71	1.65
29	4.18	3.33	2.93	2.70	2.55	2.43	2.35	2.28	2.22	2.18	2.10	2.03	1.94	1.90	1.85	1.81	1.75	1.70	1.64
30	4.17	3.32	2.92	2.69	2.53	2.42	2.33	2.27	2.21	2.16	2.09	2.01	1.93	1.89	1.84	1.79	1.74	1.68	1.62
40	4.08	3.23	2.84	2.61	2.45	2.34	2.25	2.18	2.12	2.08	2.00	1.92	1.84	1.79	1.74	1.69	1.64	1.58	1.51
60	4.00	3.15	2.76	2.53	2.37	2.25	2.17	2.10	2.04	1.99	1.92	1.84	1.75	1.70	1.65	1.59	1.53	1.47	1.39
120	3.92	3.07	2.68	2.46	2.29	2.17	2.09	2.02	1.96	1.91	1.83	1.75	1.66	1.61	1.55	1.50	1.43	1.35	1.25
∞	3.84	3.00	2.60	2.37	2.21	2.10	2.01	1.94	1.88	1.83	1.75	1.67	1.57	1.52	1.46	1.39	1.32	1.22	1.00

Table A10 Table of the F Distribution (continued) $F_{.975}$

$\frac{df_{num}}{df_{den}}$	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	047.8	700.5	864.2	899.6	921.8	937.1	948.2	956.7	963.3	968.6	976.7	984.9	993.1	997.2	1001	1006	1010	1014	1018
2	38.51	39.00	39.17	39.26	39.30	39.33	39.36	39.37	39.39	39.40	39.41	39.43	39.45	39.46	39.46	39.47	39.48	39.49	39.50
3	17.44	16.04	15.44	15.10	14.88	14.78	14.62	14.54	14.47	14.42	14.34	14.25	14.17	14.12	14.08	14.04	13.99	13.95	13.90
4	12.22	10.65	9.98	9.60	9.36	9.20	9.07	8.98	8.90	8.84	8.76	8.68	8.56	8.51	8.40	8.41	8.36	8.31	8.26
5	10.01	8.43	7.76	7.39	7.15	0.98	6.85	6.76	6.68	6.62	6.52	6.43	6.35	6.28	6.23	6.18	6.12	6.07	6.02
6	8.81	7.26	6.60	6.23	5.99	5.82	5.70	5.60	5.52	5.46	5.37	5.27	5.17	5.12	5.07	5.01	4.96	4.90	4.86
7	8.07	6.54	5.88	5.52	5.29	5.12	4.99	4.90	4.82	4.76	4.67	4.57	4.47	4.42	4.36	4.31	4.25	4.20	4.16
8	7.57	6.06	5.42	5.05	4.82	4.65	4.53	4.43	4.36	4.30	4.20	4.10	4.00	3.95	3.89	3.84	3.78	3.73	3.67
9	7.21	5.71	5.08	4.72	4.48	4.32	4.20	4.10	4.03	3.96	3.87	3.77	3.67	3.61	3.56	3.51	3.45	3.39	3.33
10	6.94	5.48	4.83	4.47	4.24	4.07	3.95	3.86	3.78	3.72	3.62	3.52	3.42	3.37	3.31	3.26	3.20	3.14	3.08
11	6.72	5.20	4.63	4.28	4.04	3.88	3.76	3.66	3.59	3.53	3.43	3.33	3.23	3.17	3.12	3.06	3.00	2.94	2.88
12	6.55	5.10	4.47	4.12	3.89	3.73	3.61	3.51	3.44	3.37	3.28	3.18	3.07	3.02	2.96	2.91	2.85	2.79	2.72
13	6.41	4.97	4.35	4.00	3.77	3.60	3.48	3.39	3.31	3.25	3.15	3.05	2.95	2.89	2.84	2.78	2.72	2.66	2.60
14	6.30	4.86	4.24	3.90	3.66	3.50	3.38	3.29	3.21	3.15	3.05	2.95	2.84	2.79	2.73	2.67	2.61	2.56	2.49
15	6.20	4.77	4.15	3.80	3.58	3.41	3.29	3.20	3.12	3.06	2.96	2.86	2.76	2.70	2.64	2.59	2.52	2.46	2.40
16	6.12	4.69	4.08	3.73	3.50	3.34	3.22	3.12	3.05	2.99	2.89	2.79	2.68	2.63	2.57	2.51	2.45	2.38	2.32
17	6.04	4.62	4.01	3.66	3.44	3.28	3.16	3.06	2.98	2.92	2.82	2.72	2.62	2.56	2.50	2.44	2.38	2.32	2.25
18	5.98	4.56	3.95	3.61	3.38	3.22	3.10	3.01	2.93	2.87	2.77	2.67	2.56	2.50	2.44	2.38	2.32	2.26	2.19
19	5.92	4.51	3.90	3.56	3.33	3.17	3.05	2.96	2.88	2.82	2.72	2.62	2.51	2.45	2.39	2.33	2.27	2.20	2.13
20	5.87	4.46	3.86	3.51	3.29	3.13	3.01	2.91	2.84	2.77	2.68	2.57	2.46	2.41	2.35	2.29	2.22	2.16	2.09
21	5.83	4.42	3.82	3.48	3.25	3.09	2.97	2.87	2.80	2.73	2.64	2.53	2.42	2.37	2.31	2.25	2.18	2.11	2.04
22	5.79	4.38	3.78	3.44	3.22	3.06	2.93	2.84	2.76	2.70	2.60	2.50	2.39	2.33	2.27	2.21	2.14	2.08	2.00
23	5.76	4.36	3.75	3.41	3.18	3.02	2.90	2.81	2.73	2.67	2.57	2.47	2.36	2.30	2.24	2.18	2.11	2.04	1.97
24	5.72	4.32	3.72	3.38	3.15	2.99	2.87	2.78	2.70	2.64	2.54	2.44	2.33	2.27	2.21	2.15	2.08	2.01	1.94
25	5.69	4.29	3.69	3.35	3.12	2.97	2.85	2.76	2.68	2.61	2.51	2.41	2.30	2.24	2.18	2.12	2.05	1.98	1.91
26	5.66	4.27	3.67	3.33	3.10	2.94	2.82	2.73	2.65	2.59	2.49	2.39	2.28	2.22	2.16	2.09	2.03	1.95	1.88
27	5.63	4.24	3.64	3.31	3.08	2.92	2.80	2.71	2.63	2.57	2.47	2.36	2.25	2.19	2.13	2.07	2.00	1.93	1.85
28	5.61	4.22	3.63	3.29	3.06	2.90	2.78	2.69	2.61	2.55	2.45	2.34	2.23	2.17	2.11	2.05	1.98	1.91	1.83
29	5.59	4.20	3.61	3.27	3.04	2.88	2.76	2.67	2.59	2.53	2.43	2.32	2.21	2.15	2.09	2.03	1.96	1.89	1.81
30	5.57	4.18	3.59	3.25	3.03	2.87	2.75	2.65	2.57	2.51	2.41	2.31	2.20	2.14	2.07	2.01	1.94	1.87	1.79
40	5.42	4.05	3.46	3.13	2.90	2.74	2.62	2.53	2.45	2.39	2.29	2.18	2.07	2.01	1.94	1.88	1.80	1.72	1.64
60	5.20	3.93	3.34	3.01	2.78	2.62	2.51	2.41	2.33	2.27	2.17	2.06	1.94	1.88	1.82	1.76	1.67	1.58	1.48
120	5.15	3.80	3.23	2.89	2.67	2.52	2.40	2.30	2.22	2.16	2.05	1.94	1.82	1.76	1.69	1.61	1.53	1.43	1.31
∞	5.02	3.69	3.12	2.79	2.57	2.41	2.29	2.19	2.11	2.05	1.94	1.83	1.71	1.64	1.57	1.48	1.39	1.27	1.00

Table A10 Table of the F Distribution (continued) $F_{.99}$

df_{num} df_{den}	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	4052	4999.5	5403	5625	5764	5859	5928	5982	6022	6050	6106	6157	6209	6235	6261	6287	6313	6339	6366
2	98.50	98.00	99.17	99.25	99.30	99.33	99.36	99.37	99.39	99.40	99.43	99.43	99.45	99.46	99.47	99.47	99.48	99.49	99.50
3	34.12	30.82	20.46	28.71	28.24	27.91	27.87	27.49	27.35	27.23	27.05	26.87	26.69	26.60	26.50	26.41	26.32	26.22	26.13
4	21.20	18.00	10.09	15.98	15.52	15.21	14.98	14.80	14.66	14.53	14.37	14.20	14.02	13.93	13.84	13.75	13.65	13.56	13.46
5	16.26	13.27	12.08	11.39	10.97	10.67	10.46	10.29	10.16	10.05	9.99	9.72	9.55	9.47	9.38	9.29	9.20	9.11	9.02
6	13.75	10.92	9.78	9.15	8.75	8.47	8.26	8.10	7.98	7.87	7.72	7.56	7.40	7.31	7.23	7.14	7.06	6.97	6.88
7	12.25	9.55	8.45	7.85	7.46	7.19	6.99	6.84	6.72	6.62	6.47	6.31	6.16	6.07	5.99	5.91	5.82	5.74	5.65
8	11.26	8.65	7.59	7.01	6.63	6.37	6.18	6.03	5.91	5.81	5.67	5.52	5.36	5.28	5.20	5.12	5.03	4.95	4.86
9	10.50	8.02	6.99	6.42	6.06	5.80	5.61	5.47	5.35	5.26	5.11	4.96	4.81	4.73	4.66	4.57	4.48	4.40	4.31
10	10.04	7.56	6.55	5.99	5.64	5.39	5.20	5.06	4.94	4.85	4.71	4.56	4.41	4.33	4.25	4.17	4.08	4.00	3.91
11	9.65	7.21	6.22	5.67	5.32	5.07	4.88	4.74	4.63	4.54	4.40	4.25	4.10	4.02	3.94	3.86	3.78	3.69	3.60
12	9.33	6.93	5.95	5.41	5.06	4.82	4.64	4.50	4.39	4.30	4.16	4.01	3.86	3.78	3.70	3.62	3.54	3.45	3.36
13	9.07	6.70	5.74	5.21	4.86	4.62	4.44	4.30	4.19	4.10	3.96	3.81	3.66	3.59	3.51	3.43	3.34	3.25	3.17
14	8.86	6.51	5.56	5.04	4.69	4.46	4.28	4.14	4.03	3.94	3.80	3.65	3.51	3.43	3.35	3.27	3.18	3.09	3.00
15	8.68	6.36	5.42	4.89	4.56	4.32	4.14	4.00	3.89	3.80	3.67	3.52	3.37	3.30	3.21	3.13	3.05	2.96	2.87
16	8.53	6.23	5.29	4.77	4.44	4.20	4.03	3.89	3.78	3.69	3.55	3.41	3.26	3.18	3.10	3.02	2.93	2.84	2.75
17	8.40	6.11	5.18	4.67	4.34	4.10	3.93	3.79	3.68	3.59	3.45	3.31	3.16	3.08	3.00	2.92	2.83	2.75	2.65
18	8.29	6.01	5.08	4.58	4.25	4.01	3.84	3.71	3.60	3.51	3.37	3.23	3.08	3.00	2.92	2.84	2.75	2.66	2.57
19	8.18	5.93	5.01	4.50	4.17	3.94	3.77	3.63	3.52	3.43	3.30	3.15	3.00	2.92	2.84	2.76	2.67	2.58	2.49
20	8.10	5.85	4.94	4.43	4.10	3.87	3.70	3.56	3.46	3.37	3.23	3.09	2.94	2.86	2.78	2.69	2.61	2.52	2.42
21	8.02	5.78	4.87	4.37	4.04	3.81	3.64	3.51	3.40	3.31	3.17	3.03	2.88	2.80	2.72	2.64	2.55	2.46	2.36
22	7.95	5.72	4.82	4.31	3.99	3.76	3.60	3.46	3.36	3.26	3.12	2.98	2.83	2.75	2.67	2.58	2.50	2.40	2.31
23	7.88	5.66	4.76	4.26	3.94	3.71	3.54	3.41	3.30	3.21	3.07	2.93	2.78	2.70	2.62	2.54	2.45	2.35	2.26
24	7.82	5.61	4.72	4.22	3.90	3.67	3.50	3.36	3.26	3.17	3.03	2.89	2.74	2.66	2.58	2.49	2.40	2.31	2.21
25	7.77	5.57	4.68	4.18	3.85	3.63	3.46	3.32	3.22	3.13	2.99	2.85	2.70	2.62	2.54	2.45	2.36	2.27	2.17
26	7.72	5.53	4.64	4.14	3.82	3.59	3.42	3.29	3.18	3.09	2.96	2.81	2.66	2.58	2.50	2.42	2.33	2.23	2.13
27	7.68	5.49	4.60	4.11	3.78	3.56	3.39	3.26	3.15	3.06	2.93	2.78	2.63	2.55	2.47	2.38	2.29	2.20	2.10
28	7.64	5.45	4.57	4.07	3.75	3.53	3.36	3.23	3.12	3.03	2.90	2.75	2.60	2.52	2.44	2.35	2.26	2.17	2.06
29	7.60	5.42	4.54	4.04	3.73	3.50	3.33	3.20	3.09	3.00	2.87	2.73	2.57	2.49	2.41	2.33	2.23	2.14	2.03
30	7.56	5.39	4.51	4.02	3.70	3.47	3.30	3.17	3.07	2.98	2.84	2.70	2.55	2.47	2.39	2.30	2.21	2.11	2.01
40	7.31	5.18	4.31	3.83	3.51	3.29	3.12	2.99	2.89	2.80	2.66	2.52	2.37	2.29	2.20	2.11	2.02	1.92	1.80
60	7.08	4.98	4.12	3.65	3.34	3.12	2.95	2.82	2.72	2.63	2.50	2.35	2.20	2.12	2.03	1.94	1.84	1.73	1.60
120	6.85	4.79	3.95	3.48	3.17	2.96	2.79	2.66	2.56	2.47	2.34	2.19	2.03	1.95	1.86	1.76	1.66	1.53	1.38
∞	6.63	4.61	3.78	3.32	3.02	2.80	2.64	2.51	2.41	2.32	2.18	2.04	1.88	1.79	1.70	1.59	1.47	1.32	1.00

Table A10 Table of the F Distribution (continued) $F_{.995}$

$\frac{df_{num}}{df_{den}}$	1	2	3	4	5	6	7	8	9	10	12	15	20	24	30	40	60	120	∞
1	162.11	200.00	216.15	225.00	230.56	234.37	237.15	239.25	240.91	242.24	244.26	246.30	248.36	249.40	250.44	251.48	252.53	253.59	254.65
2	198.5	199.0	199.2	199.2	199.3	199.3	199.4	199.4	199.4	199.4	199.4	199.4	199.4	199.5	199.5	199.5	199.5	199.5	199.5
3	55.56	49.80	47.47	46.10	45.39	44.84	44.43	44.13	43.88	43.69	43.39	43.08	42.78	42.62	42.47	42.31	42.15	41.99	41.83
4	31.33	26.28	24.24	23.15	22.46	21.97	21.62	21.35	21.14	20.97	20.70	20.44	20.17	20.03	19.89	19.75	19.61	19.47	19.32
5	22.78	18.31	16.53	15.56	14.94	14.51	14.20	13.90	13.77	13.62	13.38	13.15	12.90	12.76	12.60	12.53	12.40	12.27	12.14
6	18.03	14.54	12.92	12.03	11.46	11.07	10.79	10.57	10.39	10.25	10.03	9.81	9.59	9.47	9.36	9.24	9.12	9.00	8.88
7	16.24	13.40	10.88	10.05	9.53	9.16	8.89	8.68	8.51	8.38	8.18	7.97	7.76	7.65	7.53	7.42	7.31	7.19	7.08
8	14.69	11.04	9.60	8.81	8.30	7.93	7.69	7.50	7.34	7.21	7.01	6.81	6.61	6.50	6.40	6.29	6.18	6.06	5.96
9	13.61	10.11	8.72	7.96	7.47	7.13	6.88	6.69	6.54	6.42	6.23	6.03	5.83	5.73	5.62	5.52	5.41	5.30	5.19
10	12.83	9.43	8.08	7.34	6.87	6.54	6.30	6.12	5.97	5.85	5.66	5.47	5.27	5.17	5.07	4.97	4.86	4.75	4.64
11	12.23	8.91	7.60	6.88	6.42	6.10	5.86	5.68	5.54	5.42	5.24	5.05	4.86	4.76	4.65	4.55	4.44	4.34	4.23
12	11.75	8.51	7.23	6.52	6.07	5.76	5.52	5.35	5.20	5.09	4.91	4.72	4.53	4.43	4.33	4.23	4.12	4.01	3.90
13	11.37	8.19	6.93	6.23	5.79	5.48	5.23	5.08	4.94	4.82	4.64	4.46	4.27	4.17	4.07	3.97	3.87	3.76	3.65
14	11.06	7.92	6.68	6.00	5.56	5.26	5.03	4.86	4.72	4.60	4.43	4.25	4.06	3.96	3.86	3.76	3.66	3.55	3.44
15	10.80	7.70	6.48	5.80	5.37	5.07	4.85	4.67	4.54	4.42	4.25	4.07	3.88	3.79	3.69	3.58	3.48	3.37	3.26
16	10.58	7.51	6.30	5.64	5.21	4.91	4.69	4.52	4.38	4.27	4.10	3.92	3.73	3.64	3.54	3.44	3.33	3.22	3.11
17	10.38	7.35	6.16	5.50	5.07	4.78	4.56	4.39	4.26	4.14	3.97	3.79	3.61	3.51	3.41	3.31	3.21	3.10	2.98
18	10.23	7.21	6.03	5.37	4.95	4.66	4.44	4.28	4.14	4.03	3.86	3.68	3.50	3.40	3.30	3.20	3.10	2.99	2.87
19	10.07	7.09	5.92	5.27	4.85	4.56	4.34	4.18	4.04	3.93	3.76	3.59	3.40	3.30	3.21	3.11	3.00	2.89	2.78
20	9.94	6.99	5.82	5.17	4.76	4.47	4.26	4.09	3.96	3.85	3.68	3.50	3.32	3.22	3.12	3.02	2.92	2.81	2.69
21	9.83	6.89	5.73	5.09	4.68	4.39	4.18	4.01	3.88	3.77	3.60	3.43	3.24	3.15	3.05	2.95	2.84	2.73	2.61
22	9.73	6.81	5.65	5.02	4.61	4.32	4.11	3.94	3.81	3.70	3.54	3.36	3.18	3.08	2.98	2.88	2.77	2.66	2.55
23	9.63	6.73	5.58	4.95	4.54	4.25	4.05	3.88	3.75	3.64	3.47	3.30	3.12	3.02	2.92	2.82	2.71	2.60	2.48
24	9.55	6.66	5.52	4.89	4.49	4.20	3.99	3.83	3.69	3.59	3.42	3.25	3.06	2.97	2.87	2.77	2.66	2.55	2.43
25	9.48	6.60	5.46	4.84	4.43	4.15	3.94	3.78	3.64	3.54	3.37	3.20	3.01	2.92	2.82	2.72	2.61	2.50	2.38
26	9.41	6.54	5.41	4.79	4.38	4.10	3.89	3.73	3.60	3.49	3.33	3.15	2.97	2.87	2.77	2.67	2.56	2.45	2.33
27	9.34	6.49	5.36	4.74	4.34	4.06	3.85	3.69	3.56	3.45	3.28	3.11	2.93	2.83	2.73	2.63	2.52	2.41	2.29
28	9.28	6.44	5.32	4.70	4.30	4.02	3.81	3.65	3.52	3.41	3.25	3.07	2.89	2.79	2.69	2.60	2.48	2.37	2.24
29	9.23	6.40	5.28	4.66	4.26	3.98	3.77	3.61	3.48	3.38	3.21	3.04	2.86	2.76	2.66	2.56	2.45	2.33	2.24
30	9.18	6.36	5.24	4.62	4.23	3.95	3.74	3.58	3.45	3.34	3.18	3.01	2.82	2.73	2.63	2.52	2.42	2.30	2.18
40	8.83	6.07	4.98	4.37	3.99	3.71	3.51	3.35	3.22	3.12	2.95	2.78	2.60	2.50	2.40	2.30	2.20	2.06	1.93
60	8.49	5.79	4.73	4.14	3.76	3.49	3.29	3.13	3.01	2.90	2.74	2.57	2.39	2.29	2.20	2.08	1.96	1.83	1.69
120	8.18	5.54	4.50	3.92	3.55	3.28	3.09	2.93	2.81	2.71	2.54	2.37	2.19	2.09	1.98	1.87	1.75	1.61	1.43
∞	7.88	5.30	4.28	3.72	3.35	3.09	2.90	2.74	2.62	2.52	2.36	2.19	2.00	1.90	1.79	1.67	1.53	1.36	1.00

Table A11 Table of Critical Values for Mann-Whitney U Statistic

(Two-Tailed .05 Values)

$n_2 \backslash n_1$	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1																				
2								0	0	0	0	1	1	1	1	1	2	2	2	2
3					0	1	1	2	2	3	3	4	4	5	5	6	6	7	7	8
4				0	1	2	3	4	4	5	6	7	8	9	10	11	11	12	13	13
5			0	1	2	3	5	6	7	8	9	11	12	13	14	15	17	18	19	20
6			1	2	3	5	6	8	10	11	13	14	16	17	19	21	22	24	25	27
7			1	3	5	6	8	10	12	14	16	18	20	22	24	26	28	30	32	34
8		0	2	4	6	8	10	13	15	17	19	22	24	26	29	31	34	36	38	41
9		0	2	4	7	10	12	15	17	20	23	26	28	31	34	37	39	42	45	48
10		0	3	5	8	11	14	17	20	23	26	29	33	36	39	42	45	48	52	55
11		0	3	6	9	13	16	19	23	26	30	33	37	40	44	47	51	55	58	62
12		1	4	7	11	14	18	22	26	29	33	37	41	45	49	53	57	61	65	69
13		1	4	8	12	16	20	24	28	33	37	41	45	50	54	59	63	67	72	76
14		1	5	9	13	17	22	26	31	36	40	45	50	55	59	64	67	74	78	83
15		1	5	10	14	19	24	29	34	39	44	49	54	59	64	70	75	80	85	90
16		1	6	11	15	21	26	31	37	42	47	53	59	64	70	75	81	86	92	98
17		2	6	11	17	22	28	34	39	45	51	57	63	67	75	81	87	93	99	105
18		2	7	12	18	24	30	36	42	48	55	61	67	74	80	86	93	99	106	112
19		2	7	13	19	25	32	38	45	52	58	65	72	78	85	92	99	106	113	119
20		2	8	13	20	27	34	41	48	55	62	69	76	83	90	98	105	112	119	127

(One-Tailed .05 Values)

$n_2 \backslash n_1$	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1																			0	0
2					0	0	0	1	1	1	1	2	2	2	3	3	3	4	4	4
3			0	0	1	2	2	3	3	4	5	5	6	7	7	8	9	9	10	11
4			0	1	2	3	4	5	6	7	8	9	10	11	12	14	15	16	17	18
5		0	1	2	4	5	6	8	9	11	12	13	15	16	18	19	20	22	23	25
6		0	2	3	5	7	8	10	12	14	16	17	19	21	23	25	26	28	30	32
7		0	2	4	6	8	11	13	15	17	19	21	24	26	28	30	33	35	37	39
8		1	3	5	8	10	13	15	18	20	23	26	28	31	33	36	39	41	44	47
9		1	3	6	9	12	15	18	21	24	27	30	33	36	39	42	45	48	51	54
10		1	4	7	11	14	17	20	24	27	31	34	37	41	44	48	51	55	58	62
11		1	5	8	12	16	19	23	27	31	34	38	42	46	50	54	57	61	65	69
12		2	5	9	13	17	21	26	30	34	38	42	47	51	55	60	64	68	72	77
13		2	6	10	15	19	24	28	33	37	42	47	51	56	61	65	70	75	80	84
14		2	7	11	16	21	26	31	36	41	46	51	56	61	66	71	77	82	87	92
15		3	7	12	18	23	28	33	39	44	50	55	61	66	72	77	83	88	94	100
16		3	8	14	19	25	30	36	42	48	54	60	65	71	77	83	89	95	101	107
17		3	9	15	20	26	33	39	45	51	57	64	70	77	83	89	96	102	109	115
18		4	9	16	22	28	35	41	48	55	61	68	75	82	88	95	102	109	116	123
19	0	4	10	17	23	30	37	44	51	58	65	72	80	87	94	101	109	116	123	130
20	0	4	11	18	25	32	39	47	54	62	69	77	84	92	100	107	115	123	130	138

Table A11 Table of critical Values for Mann–Whitney *U* Statistic (continued)

(Two-Tailed .01 Values)

(Two-Tailed .01 Values)

$n_1 \backslash n_2$	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1																				
2																			0	0
3									0	0	0	1	1	1	2	2	2	2	3	3
4						0	0	1	1	2	2	3	3	4	5	5	6	6	7	8
5					0	1	1	2	3	4	5	6	7	7	8	9	10	11	12	13
6				0	1	2	3	4	5	6	7	9	10	11	12	13	15	16	17	18
7				0	1	3	4	6	7	9	10	12	13	15	16	18	19	21	22	24
8				1	2	4	6	7	9	11	13	15	17	18	20	22	24	26	28	30
9			0	1	3	5	7	9	11	13	16	18	20	22	24	27	29	31	33	36
10			0	2	4	6	9	11	13	16	18	21	24	26	29	31	34	37	39	42
11			0	2	5	7	10	13	16	18	21	24	27	30	33	36	39	42	45	48
12			1	3	6	9	12	15	18	21	24	27	31	34	37	41	44	47	51	54
13			1	3	7	10	13	17	20	24	27	31	34	38	42	45	49	53	56	60
14			1	4	7	11	15	18	22	26	30	34	38	42	46	50	54	58	63	67
15			2	5	8	12	16	20	24	29	33	37	42	46	51	55	60	64	69	73
16			2	5	9	13	18	22	27	31	36	41	45	50	55	60	65	70	74	79
17			2	6	10	15	19	24	29	34	39	44	49	54	60	65	70	75	81	86
18			2	6	11	16	21	26	31	37	42	47	53	58	64	70	75	81	87	92
19		0	3	7	12	17	22	28	33	39	45	51	56	63	69	74	81	87	93	99
20		0	3	8	13	18	24	30	36	42	48	54	60	67	73	79	86	92	99	105

(One-Tailed .01 Values)

$n_1 \backslash n_2$	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1																				
2													0	0	0	0	0	0	1	1
3							0	0	1	1	1	2	2	2	3	3	4	4	4	5
4					0	1	1	2	3	3	4	5	5	6	7	7	8	9	9	10
5				0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
6				1	2	3	4	6	7	8	9	11	12	13	15	16	18	19	20	22
7			0	1	3	4	6	7	9	11	12	14	16	17	19	21	23	24	26	28
8			0	2	4	6	7	9	11	13	15	17	20	22	24	26	28	30	32	34
9			1	3	5	7	9	11	14	16	18	21	23	26	28	31	33	36	38	40
10			1	3	6	8	11	13	16	19	22	24	27	30	33	36	38	41	44	47
11			1	4	7	9	12	15	18	22	25	28	31	34	37	41	44	47	50	53
12			2	5	8	11	14	17	21	24	28	31	35	38	42	46	49	53	56	60
13		0	2	5	9	12	16	20	23	27	31	35	39	43	47	51	55	59	63	67
14		0	2	6	10	13	17	22	26	30	34	38	43	47	51	56	60	65	69	73
15		0	3	7	11	15	19	24	28	33	37	42	47	51	56	61	66	70	75	80
16		0	3	7	12	16	21	26	31	36	41	46	51	56	61	66	71	76	82	87
17		0	4	8	13	18	23	28	33	38	44	49	55	60	66	71	77	82	88	93
18		0	4	9	14	19	24	30	36	41	47	53	59	65	70	76	82	88	94	100
19		1	4	9	15	20	26	32	38	44	50	56	63	69	75	82	88	94	101	107
20		1	5	10	16	22	28	34	40	47	53	60	67	73	80	87	93	100	107	114

Table A12 Table of Sandler's A Statistic

	One-tailed level of significance				
	.05	.025	.01	.005	.0005
	Two-tailed level of significance				
	.10	.05	.02	.01	.001
<i>df = n-1</i>					
1	.5125	.5031	.50049	.50012	.5000012
2	.412	.369	.347	.340	.334
3	.385	.324	.286	.272	.254
4	.376	.304	.257	.238	.211
5	.372	.293	.240	.218	.184
6	.370	.286	.230	.205	.167
7	.369	.281	.222	.196	.155
8	.368	.278	.217	.190	.146
9	.368	.276	.213	.185	.139
10	.368	.274	.210	.181	.134
11	.368	.273	.207	.178	.130
12	.368	.271	.205	.176	.126
13	.368	.270	.204	.174	.124
14	.368	.270	.202	.172	.121
15	.368	.269	.201	.170	.119
16	.368	.268	.200	.169	.117
17	.368	.268	.199	.168	.116
18	.368	.267	.198	.167	.114
19	.368	.267	.197	.166	.113
20	.368	.266	.197	.165	.112
21	.368	.266	.196	.165	.111
22	.368	.266	.196	.164	.110
23	.368	.266	.195	.163	.109
24	.368	.265	.195	.163	.108
25	.368	.265	.194	.162	.108
26	.368	.265	.194	.162	.107
27	.368	.265	.193	.161	.107
28	.368	.265	.193	.161	.106
29	.368	.264	.193	.161	.106
30	.368	.264	.193	.160	.105
40	.368	.263	.191	.158	.102
60	.369	.262	.189	.155	.099
120	.369	.261	.187	.153	.095
∞	.370	.260	.185	.151	.092

Table A13 Table of the Studentized Range Statistic
 $q_{.95} (\alpha = .05)$

df_{error}	k	2	3	4	5	6	7	8	9	10
1		17.97	26.98	32.82	37.08	40.41	43.12	45.40	47.36	49.07
2		6.08	8.33	9.80	10.88	11.74	12.44	13.03	13.54	13.99
3		4.50	5.91	6.82	7.50	8.04	8.48	8.85	9.18	9.46
4		3.93	5.04	5.76	6.29	6.71	7.05	7.35	7.60	7.83
5		3.64	4.60	5.22	5.67	6.03	6.33	6.58	6.80	6.99
6		3.46	4.34	4.90	5.30	5.63	5.90	6.12	6.32	6.49
7		3.34	4.16	4.68	5.06	5.36	5.61	5.82	6.00	6.16
8		3.26	4.04	4.53	4.89	5.17	5.40	5.60	5.77	5.92
9		3.20	3.95	4.41	4.76	5.02	5.24	5.43	5.59	5.74
10		3.15	3.88	4.33	4.65	4.91	5.12	5.30	5.46	5.60
11		3.11	3.82	4.26	4.57	4.82	5.03	5.20	5.35	5.49
12		3.08	3.77	4.20	4.51	4.75	4.95	5.12	5.27	5.39
13		3.06	3.73	4.15	4.45	4.69	4.88	5.05	5.19	5.32
14		3.03	3.70	4.11	4.41	4.64	4.83	4.99	5.13	5.25
15		3.01	3.67	4.08	4.37	4.59	4.78	4.94	5.08	5.20
16		3.00	3.65	4.05	4.33	4.56	4.74	4.90	5.03	5.15
17		2.98	3.63	4.02	4.30	4.52	4.70	4.86	4.99	5.11
18		2.97	3.61	4.00	4.28	4.49	4.67	4.82	4.96	5.07
19		2.96	3.59	3.98	4.25	4.47	4.65	4.79	4.92	5.04
20		2.95	3.58	3.96	4.23	4.45	4.62	4.77	4.90	5.01
24		2.92	3.53	3.90	4.17	4.37	4.54	4.68	4.81	4.92
30		2.89	3.49	3.85	4.10	4.30	4.46	4.60	4.72	4.82
40		2.86	3.44	3.79	4.04	4.23	4.39	4.52	4.63	4.73
60		2.83	3.40	3.74	3.98	4.16	4.31	4.44	4.55	4.65
120		2.80	3.36	3.68	3.92	4.10	4.24	4.36	4.47	4.56
∞		2.77	3.31	3.63	3.86	4.03	4.17	4.29	4.39	4.47

df_{error}	k	11	12	13	14	15	16	17	18	19	20
1		50.59	51.96	53.20	54.33	55.36	56.32	57.22	58.04	58.83	59.56
2		14.39	14.75	15.08	15.38	15.65	15.91	16.14	16.37	16.57	16.77
3		9.72	9.95	10.15	10.35	10.52	10.69	10.84	10.98	11.11	11.24
4		8.03	8.21	8.37	8.52	8.66	8.79	8.91	9.03	9.13	9.23
5		7.17	7.32	7.47	7.60	7.72	7.83	7.93	8.03	8.12	8.21
6		6.65	6.79	6.92	7.03	7.14	7.24	7.34	7.43	7.51	7.59
7		6.30	6.43	6.55	6.66	6.76	6.85	6.94	7.02	7.10	7.17
8		6.05	6.18	6.29	6.39	6.48	6.57	6.65	6.73	6.80	6.87
9		5.87	5.98	6.09	6.19	6.28	6.36	6.44	6.51	6.58	6.64
10		5.72	5.83	5.93	6.03	6.11	6.19	6.27	6.34	6.40	6.47
11		5.61	5.71	5.81	5.90	5.98	6.06	6.13	6.20	6.27	6.33
12		5.51	5.61	5.71	5.80	5.88	5.95	6.02	6.09	6.15	6.21
13		5.43	5.53	5.63	5.71	5.79	5.86	5.93	5.99	6.05	6.11
14		5.36	5.46	5.55	5.64	5.71	5.79	5.85	5.91	5.97	6.03
15		5.31	5.40	5.49	5.57	5.65	5.72	5.78	5.85	5.90	5.96
16		5.26	5.35	5.44	5.52	5.59	5.66	5.73	5.79	5.84	5.90
17		5.21	5.31	5.39	5.47	5.54	5.61	5.67	5.73	5.79	5.84
18		5.17	5.27	5.35	5.43	5.50	5.57	5.63	5.69	5.74	5.79
19		5.14	5.23	5.31	5.39	5.46	5.53	5.59	5.65	5.70	5.75
20		5.11	5.20	5.28	5.36	5.43	5.49	5.55	5.61	5.66	5.71
24		5.01	5.10	5.18	5.25	5.32	5.38	5.44	5.49	5.55	5.59
30		4.92	5.00	5.08	5.15	5.21	5.27	5.33	5.38	5.43	5.47
40		4.82	4.90	4.98	5.04	5.11	5.16	5.22	5.27	5.31	5.36
60		4.73	4.81	4.88	4.94	5.00	5.06	5.11	5.15	5.20	5.24
120		4.64	4.71	4.78	4.84	4.90	4.95	5.00	5.04	5.09	5.13
∞		4.55	4.62	4.68	4.74	4.80	4.85	4.89	4.93	4.97	5.01

Table A13 Table of the Studentized Range Statistic (continued)
 $q_{.99} (\alpha = .01)$

df_{error}	k	2	3	4	5	6	7	8	9	10
1		90.03	135.0	164.3	185.6	202.2	215.8	227.2	237.0	245.6
2		14.04	19.02	22.29	24.72	26.63	28.20	29.53	30.68	31.69
3		8.26	10.62	12.17	13.33	14.24	15.00	15.64	16.20	16.69
4		6.51	8.12	9.17	9.96	10.58	11.10	11.55	11.93	12.27
5		5.70	6.98	7.80	8.42	8.91	9.32	9.67	9.97	10.24
6		5.24	6.33	7.03	7.56	7.97	8.32	8.61	8.87	9.10
7		4.95	5.92	6.54	7.01	7.37	7.68	7.94	8.17	8.37
8		4.75	5.64	6.20	6.62	6.96	7.24	7.47	7.68	7.86
9		4.60	5.43	5.96	6.35	6.66	6.91	7.13	7.33	7.49
10		4.48	5.27	5.77	6.14	6.43	6.67	6.87	7.05	7.21
11		4.39	5.15	5.62	5.97	6.25	6.48	6.67	6.84	6.99
12		4.32	5.05	5.50	5.84	6.10	6.32	6.51	6.67	6.81
13		4.26	4.96	5.40	5.73	5.98	6.19	6.37	6.53	6.67
14		4.21	4.89	5.32	5.63	5.88	6.08	6.26	6.41	6.54
15		4.17	4.84	5.25	5.56	5.80	5.99	6.16	6.31	6.44
16		4.13	4.79	5.19	5.49	5.72	5.92	6.08	6.22	6.35
17		4.10	4.74	5.14	5.43	5.66	5.85	6.01	6.15	6.27
18		4.07	4.70	5.09	5.38	5.60	5.79	5.94	6.08	6.20
19		4.05	4.67	5.05	5.33	5.55	5.73	5.89	6.02	6.14
20		4.02	4.64	5.02	5.29	5.51	5.69	5.84	5.97	6.09
24		3.96	4.55	4.91	5.17	5.37	5.54	5.69	5.81	5.92
30		3.89	4.45	4.80	5.05	5.24	5.40	5.54	5.65	5.76
40		3.82	4.37	4.70	4.93	5.11	5.26	5.39	5.50	5.60
60		3.76	4.28	4.59	4.82	4.99	5.13	5.25	5.36	5.45
120		3.70	4.20	4.50	4.71	4.87	5.01	5.12	5.21	5.30
∞		3.64	4.12	4.40	4.60	4.76	4.88	4.99	5.08	5.16

df_{error}	k	11	12	13	14	15	16	17	18	19	20
1		253.2	260.0	266.2	271.8	277.0	281.8	286.3	290.4	294.3	298.0
2		32.59	33.40	34.13	34.81	35.43	36.00	36.53	37.03	37.50	37.95
3		17.13	17.53	17.89	18.22	18.52	18.81	19.07	19.32	19.55	19.77
4		12.57	12.84	13.09	13.32	13.53	13.73	13.91	14.08	14.24	14.40
5		10.48	10.70	10.89	11.08	11.24	11.40	11.55	11.68	11.81	11.93
6		9.30	9.48	9.65	9.81	9.95	10.08	10.21	10.32	10.43	10.54
7		8.55	8.71	8.86	9.00	9.12	9.24	9.35	9.46	9.55	9.65
8		8.03	8.18	8.31	8.44	8.55	8.66	8.76	8.85	8.94	9.03
9		7.65	7.78	7.91	8.03	8.13	8.23	8.33	8.41	8.49	8.57
10		7.36	7.49	7.60	7.71	7.81	7.91	7.99	8.08	8.15	8.23
11		7.13	7.25	7.36	7.46	7.56	7.65	7.73	7.81	7.88	7.95
12		6.94	7.06	7.17	7.26	7.36	7.44	7.52	7.59	7.66	7.73
13		6.79	6.90	7.01	7.10	7.19	7.27	7.35	7.42	7.48	7.55
14		6.66	6.77	6.87	6.96	7.05	7.13	7.20	7.27	7.33	7.39
15		6.55	6.66	6.76	6.84	6.93	7.00	7.07	7.14	7.20	7.26
16		6.46	6.56	6.66	6.74	6.82	6.90	6.97	7.03	7.09	7.15
17		6.38	6.48	6.57	6.66	6.73	6.81	6.87	6.94	7.00	7.05
18		6.31	6.41	6.50	6.58	6.65	6.73	6.79	6.85	6.91	6.97
19		6.25	6.34	6.43	6.51	6.58	6.65	6.72	6.78	6.84	6.89
20		6.19	6.28	6.37	6.45	6.52	6.59	6.65	6.71	6.77	6.82
24		6.02	6.11	6.19	6.26	6.33	6.39	6.45	6.51	6.56	6.61
30		5.85	5.93	6.01	6.08	6.14	6.20	6.26	6.31	6.36	6.41
40		5.69	5.76	5.83	5.90	5.96	6.02	6.07	6.12	6.16	6.21
60		5.53	5.60	5.67	5.73	5.78	5.84	5.89	5.93	5.97	6.01
120		5.37	5.44	5.50	5.56	5.61	5.66	5.71	5.75	5.79	5.83
∞		5.23	5.29	5.35	5.40	5.45	5.49	5.54	5.57	5.61	5.65

Table A14 Table of Dunnett's Modified t Statistic for a Control Group Comparison
Two-Tailed Values

The .05 critical values are in lightface type, and the .01 critical values are in **bold** type.

$k = \text{number of treatment means, including control}$									
df_{error}	2	3	4	5	6	7	8	9	10
5	2.57 4.03	3.03 4.63	3.29 4.98	3.48 5.22	3.62 5.41	3.73 5.56	3.82 5.69	3.90 5.80	3.97 5.89
6	2.45 3.71	2.86 4.21	3.10 4.51	3.26 4.71	3.39 4.87	3.49 5.00	3.57 5.10	3.64 5.20	3.71 5.28
7	2.36 3.50	2.75 3.95	2.97 4.21	3.12 4.39	3.24 4.53	3.33 4.64	3.41 4.74	3.47 4.82	3.53 4.89
8	2.31 3.36	2.67 3.77	2.88 4.00	3.02 4.17	3.13 4.29	3.22 4.40	3.29 4.48	3.35 4.56	3.41 4.62
9	2.26 3.25	2.61 3.63	2.81 3.85	2.95 4.01	3.05 4.12	3.14 4.22	3.20 4.30	3.26 4.37	3.32 4.43
10	2.23 3.17	2.57 3.53	2.76 3.74	2.89 3.88	2.99 3.99	3.07 4.08	3.14 4.16	3.19 4.22	3.24 4.28
11	2.20 3.11	2.53 3.45	2.72 3.65	2.84 3.79	2.94 3.89	3.02 3.98	3.08 4.05	3.14 4.11	3.19 4.16
12	2.18 3.05	2.50 3.39	2.68 3.58	2.81 3.71	2.90 3.81	2.98 3.89	3.04 3.96	3.09 4.02	3.14 4.07
13	2.16 3.01	2.48 3.33	2.65 3.52	2.78 3.65	2.87 3.74	2.94 3.82	3.00 3.89	3.06 3.94	3.10 3.99
14	2.14 2.98	2.46 3.29	2.63 3.47	2.75 3.59	2.84 3.69	2.91 3.76	2.97 3.83	3.02 3.88	3.07 3.93
15	2.13 2.95	2.44 3.25	2.61 3.43	2.73 3.55	2.82 3.64	2.89 3.71	2.95 3.78	3.00 3.83	3.04 3.88
16	2.12 2.92	2.42 3.22	2.59 3.39	2.71 3.51	2.80 3.60	2.87 3.67	2.92 3.73	2.97 3.78	3.02 3.83
17	2.11 2.90	2.41 3.19	2.58 3.36	2.69 3.47	2.78 3.56	2.85 3.63	2.90 3.69	2.95 3.74	3.00 3.79
18	2.10 2.88	2.40 3.17	2.56 3.33	2.68 3.44	2.76 3.53	2.83 3.60	2.89 3.66	2.94 3.71	2.98 3.75
19	2.09 2.86	2.39 3.15	2.55 3.31	2.66 3.42	2.75 3.50	2.81 3.57	2.87 3.63	2.92 3.68	2.96 3.72
20	2.09 2.85	2.38 3.13	2.54 3.29	2.65 3.40	2.73 3.48	2.80 3.55	2.86 3.60	2.90 3.65	2.95 3.69
24	2.06 2.80	2.35 3.07	2.51 3.22	2.61 3.32	2.70 3.40	2.76 3.47	2.81 3.52	2.86 3.57	2.90 3.61
30	2.04 2.75	2.32 3.01	2.47 3.15	2.58 3.25	2.66 3.33	2.72 3.39	2.77 3.44	2.82 3.49	2.86 3.52
40	2.02 2.70	2.29 2.95	2.44 3.09	2.54 3.19	2.62 3.26	2.68 3.32	2.73 3.37	2.77 3.41	2.81 3.44
60	2.00 2.66	2.27 2.90	2.41 3.03	2.51 3.12	2.58 3.19	2.64 3.25	2.69 3.29	2.73 3.33	2.77 3.37
120	1.98 2.62	2.24 2.85	2.38 2.97	2.47 3.06	2.55 3.12	2.60 3.18	2.65 3.22	2.69 3.26	2.73 3.29
∞	1.96 2.58	2.21 2.79	2.35 2.92	2.44 3.00	2.51 3.06	2.57 3.11	2.61 3.15	2.65 3.19	2.69 3.22

Table A14 Table of Dunnett’s Modified t Statistic for a Control Group Comparison
(continued)

One-Tailed Values

<i>k</i> = number of treatment means, including control									
<i>df</i> _{error}	2	3	4	5	6	7	8	9	10
5	2.02	2.44	2.68	2.85	2.98	3.08	3.16	3.24	3.30
	3.37	3.90	4.21	4.43	4.60	4.73	4.85	4.94	5.03
6	1.94	2.34	2.56	2.71	2.83	2.92	3.00	3.07	3.12
	3.14	3.61	3.88	4.07	4.21	4.33	4.43	4.51	4.59
7	1.89	2.27	2.48	2.62	2.73	2.82	2.89	2.95	3.01
	3.00	3.42	3.66	3.83	3.96	4.07	4.15	4.23	4.30
8	1.86	2.22	2.42	2.55	2.66	2.74	2.81	2.87	2.92
	2.90	3.29	3.51	3.67	3.79	3.88	3.96	4.03	4.09
9	1.83	2.18	2.37	2.50	2.20	2.68	2.75	2.81	2.86
	2.82	3.19	3.40	3.55	3.66	3.75	3.82	3.89	3.94
10	1.81	2.15	2.34	2.47	2.56	2.64	2.70	2.76	2.81
	2.76	3.11	3.31	3.45	3.56	3.64	3.71	3.78	3.83
11	1.80	2.13	2.31	2.44	2.53	2.60	2.67	2.72	2.77
	2.72	3.06	3.25	3.38	3.48	3.56	3.63	3.69	3.74
12	1.78	2.11	2.29	2.41	2.50	2.58	2.64	2.69	2.74
	2.68	3.01	3.19	3.32	3.42	3.50	3.56	3.62	3.67
13	1.77	2.09	2.27	2.39	2.48	2.55	2.61	2.66	2.71
	2.65	2.97	3.15	3.27	3.37	3.44	3.51	3.56	3.61
14	1.76	2.08	2.25	2.37	2.46	2.53	2.59	2.64	2.69
	2.62	2.94	3.11	3.23	3.32	3.40	3.46	3.51	3.56
15	1.75	2.07	2.24	2.36	2.44	2.51	2.57	2.62	2.67
	2.60	2.91	3.08	3.20	3.29	3.36	3.42	3.47	3.52
16	1.75	2.06	2.23	2.34	2.43	2.50	2.56	2.61	2.65
	2.58	2.88	3.05	3.17	3.26	3.33	3.39	3.44	3.48
17	1.74	2.05	2.22	2.33	2.42	2.49	2.54	2.59	2.64
	2.57	2.86	3.03	3.14	3.23	3.30	3.36	3.41	3.45
18	1.73	2.04	2.21	2.32	2.41	2.48	2.53	2.58	2.62
	2.55	2.84	3.01	3.12	3.21	3.27	3.33	3.38	3.42
19	1.73	2.03	2.20	2.31	2.40	2.47	2.52	2.57	2.61
	2.54	2.83	2.99	3.10	3.18	3.25	3.31	3.36	3.40
20	1.72	2.03	2.19	2.30	2.39	2.46	2.51	2.56	2.60
	2.53	2.81	2.97	3.08	3.17	3.23	3.29	3.34	3.38
24	1.71	2.01	2.17	2.28	2.36	2.43	2.48	2.53	2.57
	2.49	2.77	2.92	3.03	3.11	3.17	3.22	3.27	3.31
30	1.70	1.99	2.15	2.25	2.33	2.40	2.45	2.50	2.54
	2.46	2.72	2.87	2.97	3.05	3.11	3.16	3.21	3.24
40	1.68	1.97	2.13	2.23	2.31	2.37	2.42	2.47	2.51
	2.42	2.68	2.82	2.92	2.99	3.05	3.10	3.14	3.18
60	1.67	1.95	2.10	2.21	2.28	2.35	2.39	2.44	2.48
	2.39	2.64	2.78	2.87	2.94	3.00	3.04	3.08	3.12
120	1.66	1.93	2.08	2.18	2.26	2.32	2.37	2.41	2.45
	2.36	2.60	2.73	2.82	2.89	2.94	2.99	3.03	3.06
∞	1.64	1.92	2.06	2.16	2.23	2.29	2.34	2.38	2.42
	2.33	2.56	2.68	2.77	2.84	2.89	2.93	2.97	3.00

Table A15 Graphs of the Power Function for the Analysis of Variance
(Fixed-Effects Model)

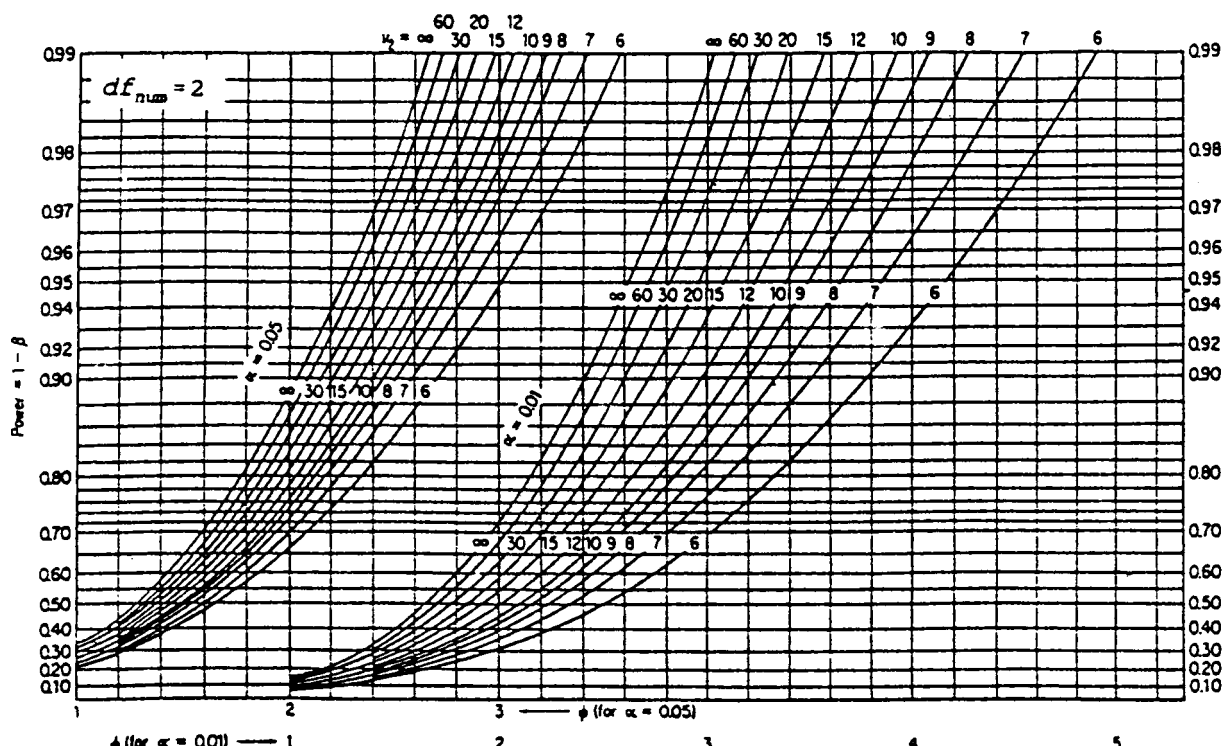
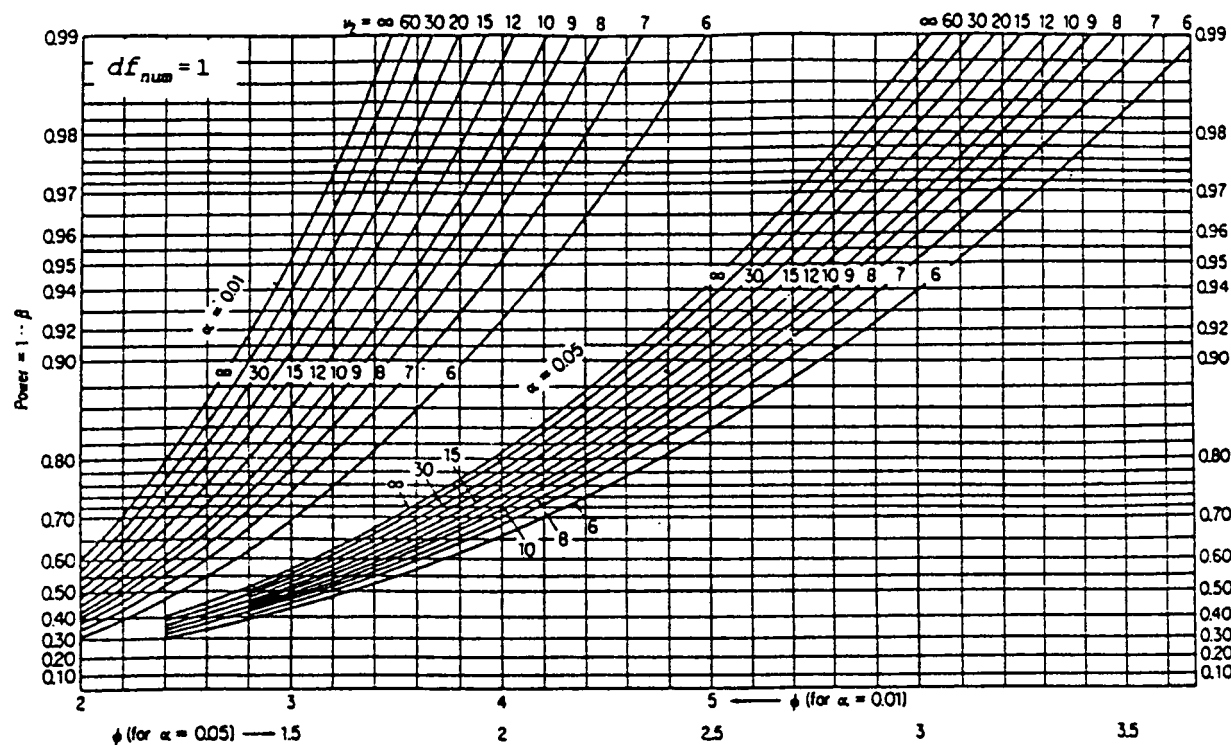


Table A15 Graphs of the Power Function for the Analysis of Variance (continued)

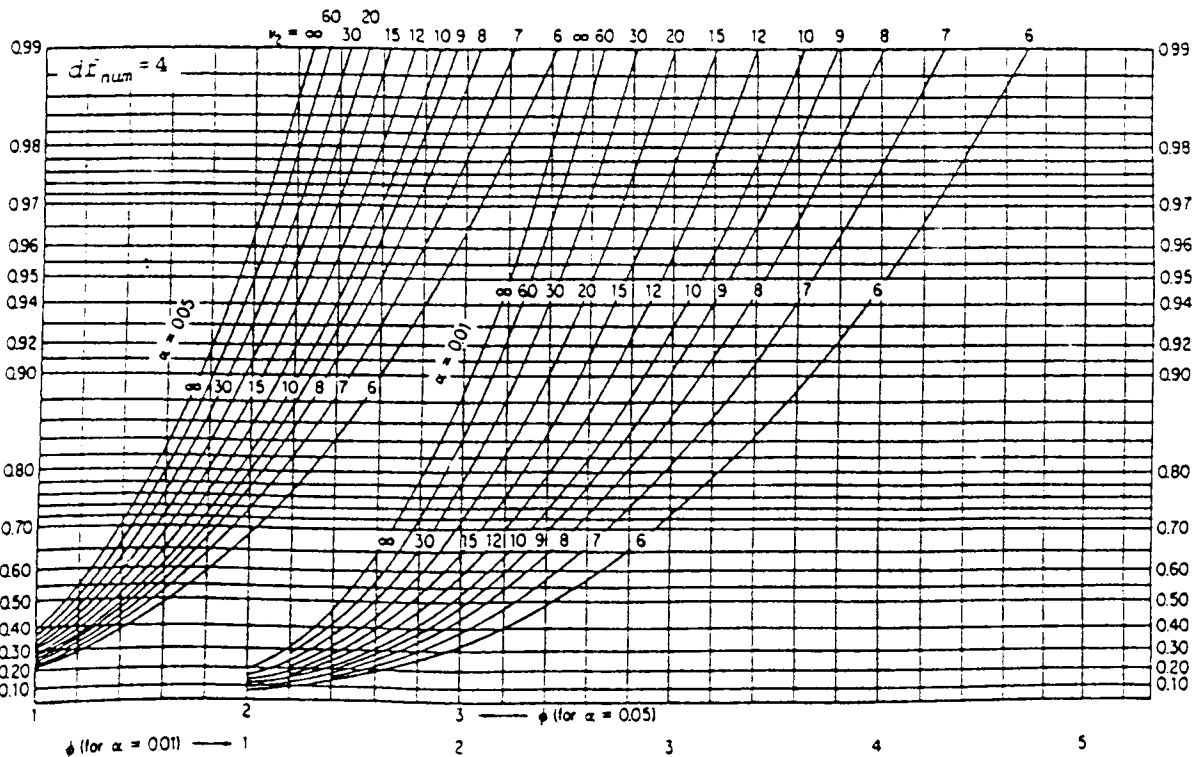
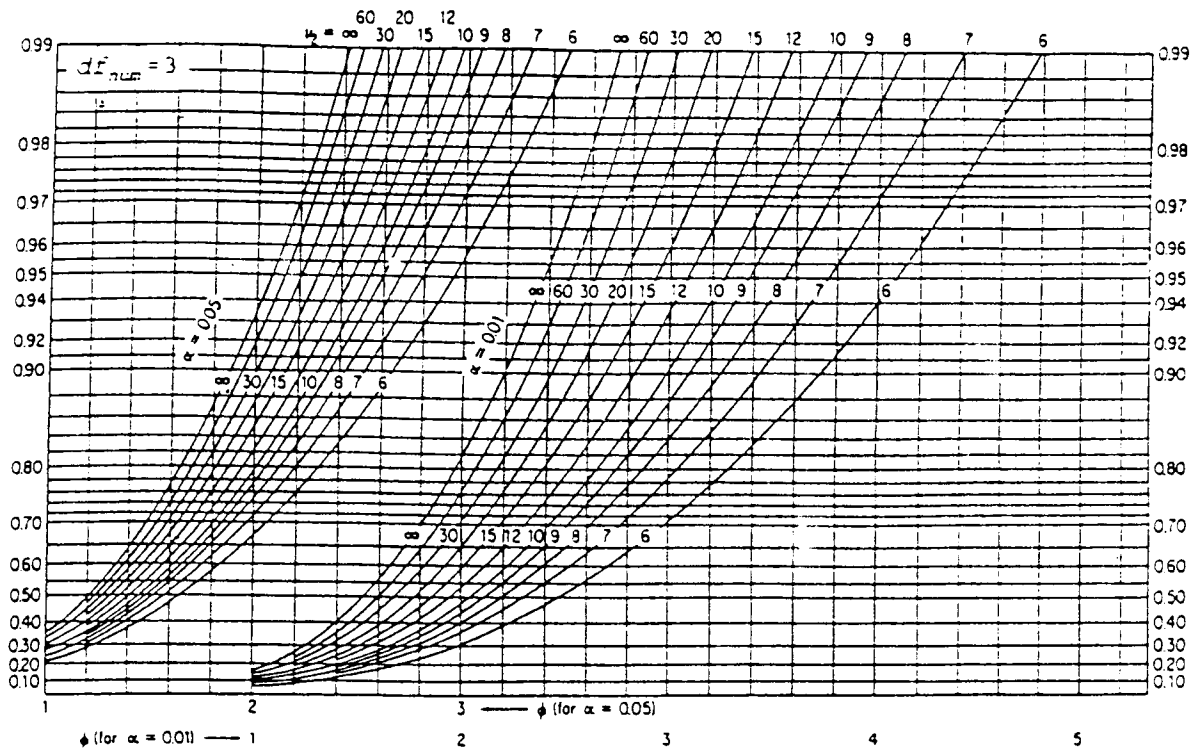


Table A15 Graphs of the Power Function for the Analysis of Variance (continued)

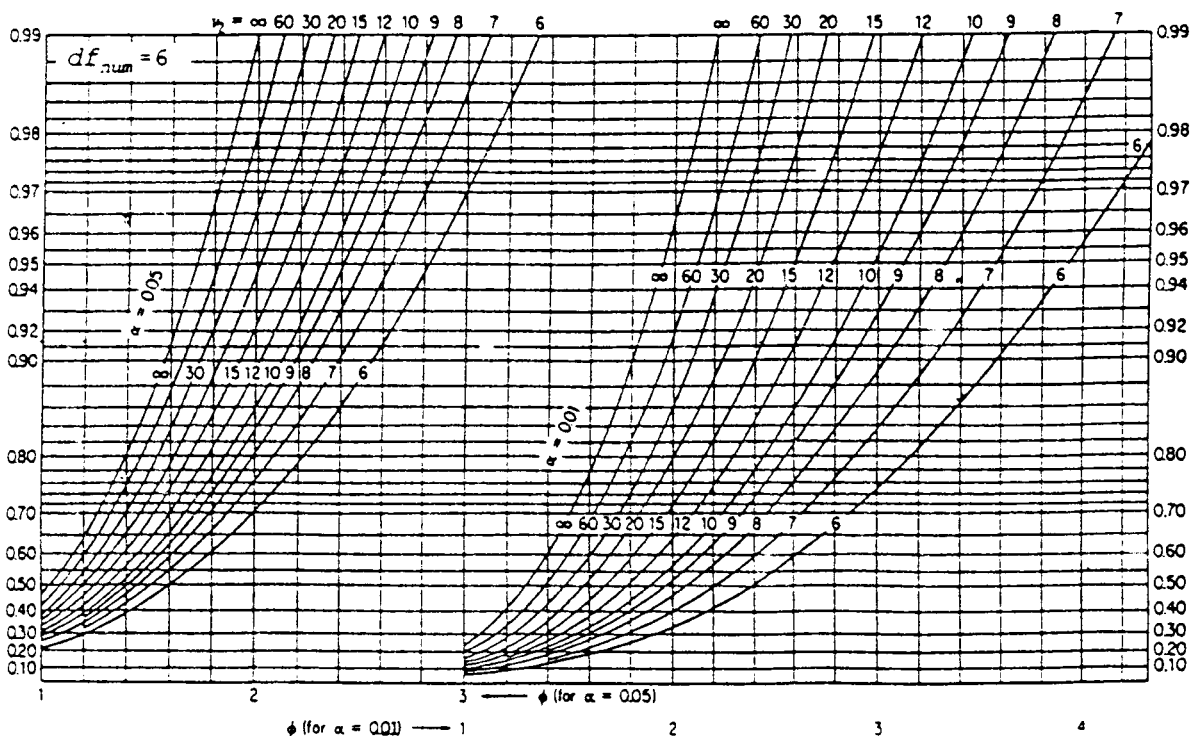
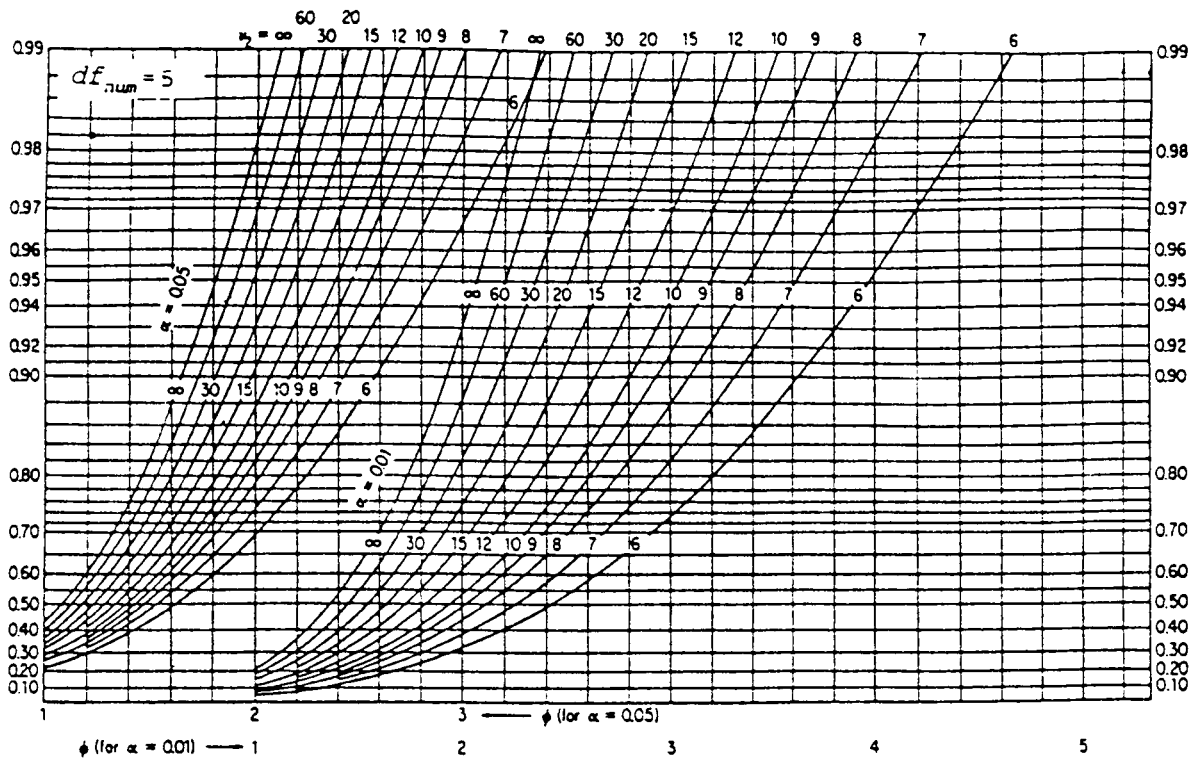


Table A15 Graphs of the Power Function for the Analysis of Variance (continued)

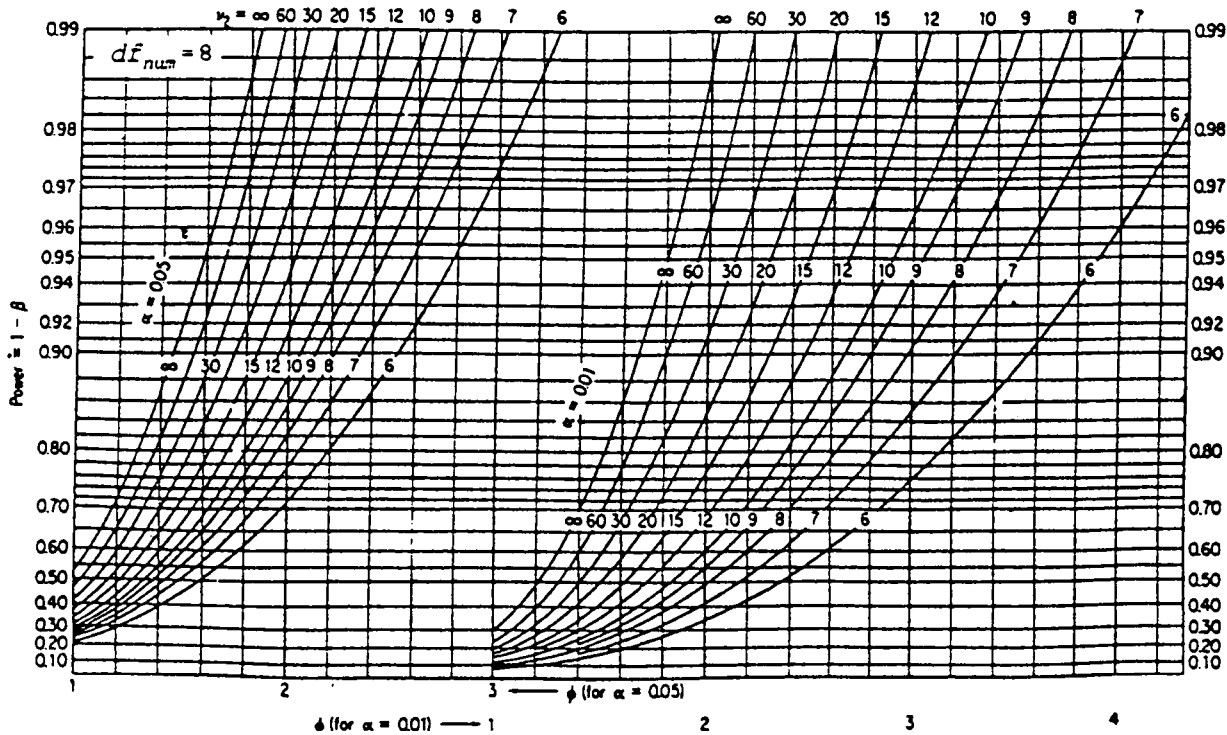
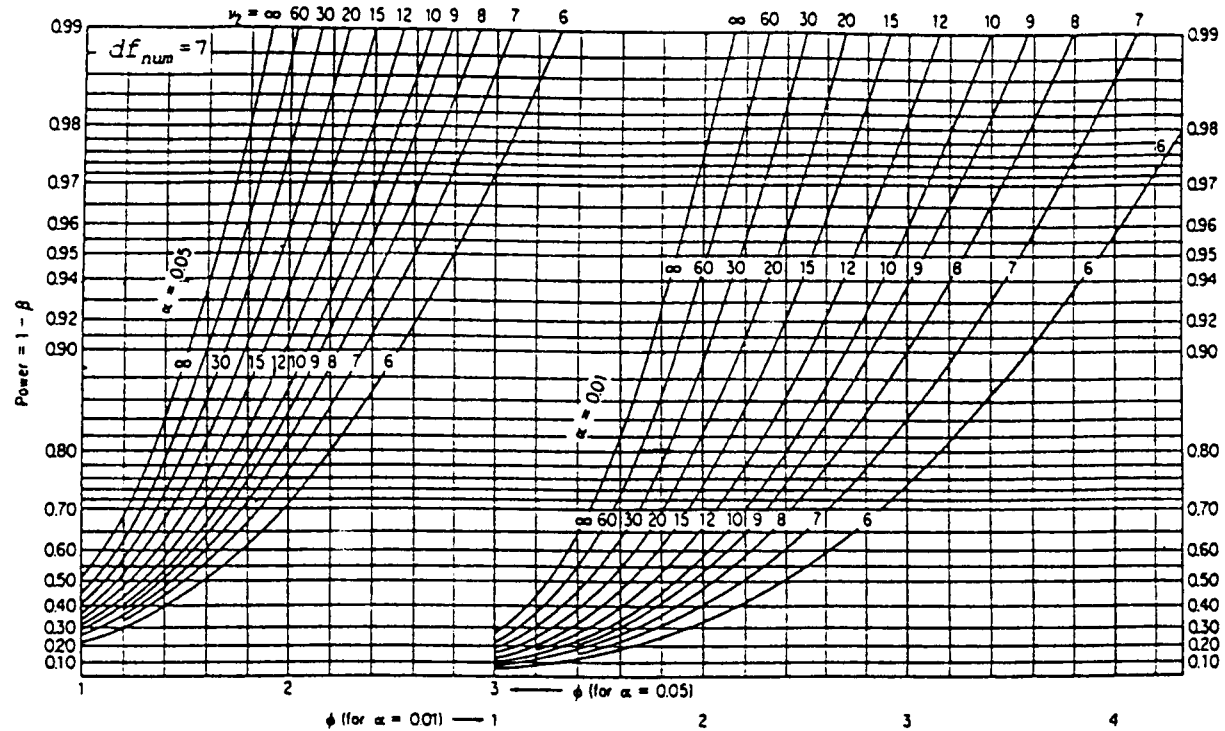


Table A16 Table of Critical Values for Pearson r

	One-tailed level of significance			
	.05	.025	.01	.005
	Two-tailed level of significance			
	.10	.05	.02	.01
<i>df = n-2</i>				
1	.988	.997	.9995	.9999
2	.900	.950	.980	.990
3	.805	.878	.934	.959
4	.729	.811	.882	.917
5	.669	.754	.833	.874
6	.622	.707	.789	.834
7	.582	.666	.750	.798
8	.549	.632	.716	.765
9	.521	.602	.685	.735
10	.497	.576	.658	.708
11	.476	.553	.634	.684
12	.458	.532	.612	.661
13	.441	.514	.592	.641
14	.426	.497	.574	.623
15	.412	.482	.558	.606
16	.400	.468	.542	.590
17	.389	.456	.528	.575
18	.378	.444	.516	.561
19	.369	.433	.503	.549
20	.360	.423	.492	.537
21	.352	.413	.482	.526
22	.344	.404	.472	.515
23	.337	.396	.462	.505
24	.330	.388	.453	.496
25	.323	.381	.445	.487
26	.317	.374	.437	.479
27	.311	.367	.430	.471
28	.306	.361	.423	.463
29	.301	.355	.416	.456
30	.296	.349	.409	.449
35	.275	.325	.381	.418
40	.257	.304	.358	.393
45	.243	.288	.338	.372
50	.231	.273	.322	.354
60	.211	.250	.295	.325
70	.195	.232	.274	.302
80	.183	.217	.256	.283
90	.173	.205	.242	.267
100	.164	.195	.230	.254

Table A17 Table of Fisher's z_r Transformation

r	z_r	r	z_r	r	z_r	r	z_r	r	z_r
.000	.000	.200	.203	.400	.424	.600	.693	.800	1.099
.005	.005	.205	.208	.405	.430	.605	.701	.805	1.113
.010	.010	.210	.213	.410	.436	.610	.709	.810	1.127
.015	.015	.215	.218	.415	.442	.615	.717	.815	1.142
.020	.020	.220	.224	.420	.448	.620	.725	.820	1.157
.025	.025	.225	.229	.425	.454	.625	.733	.825	1.172
.030	.030	.230	.234	.430	.460	.630	.741	.830	1.188
.035	.035	.235	.239	.435	.466	.635	.750	.835	1.204
.040	.040	.240	.245	.440	.472	.640	.758	.840	1.221
.045	.045	.245	.250	.445	.478	.645	.767	.845	1.238
.050	.050	.250	.255	.450	.485	.650	.775	.850	1.256
.055	.055	.255	.261	.455	.491	.655	.784	.855	1.274
.060	.060	.260	.266	.460	.497	.660	.793	.860	1.293
.065	.065	.265	.271	.465	.504	.665	.802	.865	1.313
.070	.070	.270	.277	.470	.510	.670	.811	.870	1.333
.075	.075	.275	.282	.475	.517	.675	.820	.875	1.354
.080	.080	.280	.288	.480	.523	.680	.829	.880	1.376
.085	.085	.285	.293	.485	.530	.685	.838	.885	1.398
.090	.090	.290	.299	.490	.536	.690	.848	.890	1.422
.095	.095	.295	.304	.495	.543	.695	.858	.895	1.447
.100	.100	.300	.310	.500	.549	.700	.867	.900	1.472
.105	.105	.305	.315	.505	.556	.705	.877	.905	1.499
.110	.110	.310	.321	.510	.563	.710	.887	.910	1.528
.115	.116	.315	.326	.515	.570	.715	.897	.915	1.557
.120	.121	.320	.332	.520	.576	.720	.908	.920	1.589
.125	.126	.325	.337	.525	.583	.725	.918	.925	1.623
.130	.131	.330	.343	.530	.590	.730	.929	.930	1.658
.135	.136	.335	.348	.535	.597	.735	.940	.935	1.697
.140	.141	.340	.354	.540	.604	.740	.950	.940	1.738
.145	.146	.345	.360	.545	.611	.745	.962	.945	1.783
.150	.151	.350	.365	.550	.618	.750	.973	.950	1.832
.155	.156	.355	.371	.555	.626	.755	.984	.955	1.886
.160	.161	.360	.377	.560	.633	.760	.996	.960	1.946
.165	.167	.365	.383	.565	.640	.765	1.008	.965	2.014
.170	.172	.370	.388	.570	.648	.770	1.020	.970	2.092
.175	.177	.375	.394	.575	.655	.775	1.033	.975	2.185
.180	.182	.380	.400	.580	.662	.780	1.045	.980	2.298
.185	.187	.385	.406	.585	.670	.785	1.058	.985	2.443
.190	.192	.390	.412	.590	.678	.790	1.071	.990	2.647
.195	.198	.395	.418	.595	.685	.795	1.085	.995	2.994

Table A18 Table of Critical Values for Spearman's Rho

<i>n</i>	One-tailed level of significance			
	.05	.025	.01	.005
	Two-tailed level of significance			
	.10	.05	.02	.01
4	1.000	—	—	—
5	.900	1.000	1.000	—
6	.829	.886	.943	1.000
7	.714	.786	.893	.929
8	.643	.738	.833	.881
9	.600	.700	.783	.833
10	.564	.648	.745	.794
11	.536	.618	.709	.755
12	.503	.587	.671	.727
13	.484	.560	.648	.703
14	.464	.538	.622	.675
15	.443	.521	.604	.654
16	.429	.503	.582	.635
17	.414	.485	.566	.615
18	.401	.472	.550	.600
19	.391	.460	.535	.584
20	.380	.447	.520	.570
21	.370	.435	.508	.556
22	.361	.425	.496	.544
23	.353	.415	.486	.532
24	.344	.406	.476	.521
25	.337	.398	.466	.511
26	.331	.390	.457	.501
27	.324	.382	.448	.491
28	.317	.375	.440	.483
29	.312	.368	.433	.475
30	.306	.362	.425	.467
35	.283	.335	.394	.433
40	.264	.313	.368	.405
45	.248	.294	.347	.382
50	.235	.279	.329	.363
60	.214	.255	.300	.331
70	.190	.235	.278	.307
80	.185	.220	.260	.287
90	.174	.207	.245	.271
100	.165	.197	.233	.257

Table A19 Table of Critical Values for Kendall's Tau

Critical values for both $\bar{\tau}$ and S are listed in the table.

Two-tailed One tailed	.01 .005		.02 .01		.05 .025		.10 .05		.20 .10	
	n	S	$\bar{\tau}$	S	$\bar{\tau}$	S	$\bar{\tau}$	S	$\bar{\tau}$	S
	4	8	1.000	8	1.000	8	1.000	6	1.000	6
	5	12	1.000	10	1.000	10	.800	8	.800	8
	6	15	1.000	13	.867	13	.733	9	.600	9
	7	19	.905	17	.810	15	.619	11	.524	11
	8	22	.786	20	.714	18	.571	12	.429	12
	9	26	.722	24	.667	20	.556	18	.500	14
	10	29	.644	27	.600	23	.511	21	.467	17
	11	33	.600	31	.564	27	.491	23	.418	19
	12	38	.576	36	.545	30	.455	26	.394	20
	13	44	.564	40	.513	34	.436	28	.359	24
	14	47	.516	43	.473	37	.407	33	.363	25
	15	53	.505	49	.467	41	.390	35	.333	29
	16	58	.483	52	.433	46	.383	38	.317	30
	17	64	.471	58	.426	50	.368	42	.309	34
	18	69	.451	63	.412	53	.346	45	.294	37
	19	75	.439	67	.392	57	.333	49	.287	39
	20	80	.421	72	.379	62	.326	52	.274	42
	21	86	.410	78	.371	66	.314	56	.267	44
	22	91	.394	83	.359	71	.307	61	.264	47
	23	99	.391	89	.352	75	.296	65	.257	51
	24	104	.377	94	.341	80	.290	68	.246	54
	25	110	.367	100	.333	86	.287	72	.240	58
	26	117	.360	107	.329	91	.280	77	.237	61
	27	125	.356	113	.322	95	.271	81	.231	63
	28	130	.344	118	.312	100	.265	86	.228	68
	29	138	.340	126	.310	106	.261	90	.222	70
	30	145	.333	131	.301	111	.255	95	.218	75
	31	151	.325	137	.295	117	.252	99	.213	77
	32	160	.323	144	.290	122	.246	104	.210	82
	33	166	.314	152	.288	128	.242	108	.205	86
	34	175	.312	157	.280	133	.237	113	.201	89
	35	181	.304	165	.277	139	.234	117	.197	93
	36	190	.302	172	.273	146	.232	122	.194	96
	37	198	.297	178	.267	152	.228	128	.192	100
	38	205	.292	185	.263	157	.223	133	.189	105
	39	213	.287	193	.260	163	.220	139	.188	109
	40	222	.285	200	.256	170	.218	144	.185	112

Table A20 Table of Critical Values for Kendall's Coefficient of Concordance

Critical values for both S and \tilde{W} are listed. The values of \tilde{W} in the table were computed by substituting the tabled S values in Equation 31.3.

	<i>n</i>									
<i>m</i>	3		4		5		6		7	
Values at .05 level of significance										
	<i>S</i>	\tilde{W}	<i>S</i>	\tilde{W}	<i>S</i>	\tilde{W}	<i>S</i>	\tilde{W}	<i>S</i>	\tilde{W}
3					64.4	.716	103.9	.660	157.3	.624
4			49.5	.619	88.4	.552	143.3	.512	217.0	.484
5			62.6	.501	112.3	.449	182.4	.417	276.2	.395
6			75.7	.421	136.1	.378	221.4	.351	335.2	.333
8	48.1	.376	101.7	.318	183.7	.287	299.0	.267	453.1	.253
10	60.0	.300	127.8	.256	231.2	.231	376.7	.215	571.0	.204
15	89.8	.200	192.9	.171	349.8	.155	570.5	.145	864.9	.137
20	119.7	.150	258.0	.129	468.5	.117	764.4	.109	1158.7	.103
Values at .01 level of significance										
3					75.6	.840	122.8	.780	185.6	.737
4			61.4	.768	109.3	.683	176.2	.629	265.0	.592
5			80.5	.644	142.8	.571	229.4	.524	343.8	.491
6			99.5	.553	176.1	.489	282.4	.448	422.6	.419
8	66.8	.522	137.4	.429	242.7	.379	388.3	.347	579.9	.324
10	85.1	.425	175.3	.351	309.1	.309	494.0	.282	737.0	.263
15	131.0	.291	269.8	.240	475.2	.211	758.2	.193	1129.5	.179
20	177.0	.221	364.2	.182	641.2	.160	1022.2	.146	1521.9	.136

Additional values for $n = 3$

<i>m</i>	At .05 level		At .01 level	
	<i>S</i>	\tilde{W}	<i>S</i>	\tilde{W}
9	54.0	.333	75.9	.469
12	71.9	.250	103.5	.359
14	83.8	.214	121.9	.311
16	95.8	.187	140.2	.274
18	107.7	.166	158.6	.245

**Table A21 Table of Critical Values for the Kolmogorov–Smirnov
Goodness-of-Fit Test for a Single Sample**

One-tailed	.10	.05	.025	.01	.005
Two-tailed	.20	.10	.050	.02	.010
<i>n</i> = 1	.900	.950	.975	.990	.995
2	.684	.776	.842	.900	.929
3	.565	.636	.708	.785	.829
4	.493	.565	.624	.689	.734
5	.447	.509	.563	.627	.669
6	.410	.468	.519	.577	.617
7	.381	.436	.483	.538	.576
8	.358	.410	.454	.507	.542
9	.339	.387	.430	.480	.513
10	.323	.369	.409	.457	.489
11	.308	.352	.391	.437	.468
12	.296	.338	.375	.419	.449
13	.285	.325	.361	.404	.432
14	.275	.314	.349	.390	.418
15	.266	.304	.338	.377	.404
16	.258	.295	.327	.366	.392
17	.250	.286	.318	.355	.381
18	.244	.279	.309	.346	.371
19	.237	.271	.301	.337	.361
20	.232	.265	.294	.329	.352
21	.226	.259	.287	.321	.344
22	.221	.253	.281	.314	.337
23	.216	.247	.275	.307	.330
24	.212	.242	.269	.301	.323
25	.208	.238	.264	.295	.317
26	.204	.233	.259	.290	.311
27	.200	.229	.254	.284	.305
28	.197	.225	.250	.279	.300
29	.193	.221	.246	.275	.295
30	.190	.218	.242	.270	.290
31	.187	.214	.238	.266	.285
32	.184	.211	.234	.262	.281
33	.182	.208	.231	.258	.277
34	.179	.205	.227	.254	.273
35	.177	.202	.224	.251	.269
36	.174	.199	.221	.247	.265
37	.172	.196	.218	.244	.262
38	.170	.194	.215	.241	.258
39	.168	.191	.213	.238	.255
40	.165	.189	.210	.235	.252
<i>n</i> > 40	$1.07/\sqrt{n}$	$1.22/\sqrt{n}$	$1.36/\sqrt{n}$	$1.52/\sqrt{n}$	$1.63/\sqrt{n}$

Table A22 Table of Critical Values for the Lilliefors Test for Normality

One-tailed	.20	.15	.10	.05	.01
Two-tailed	.40	.30	.20	.10	.02
$n = 4$.300	.319	.352	.381	.417
5	.285	.299	.315	.337	.405
6	.265	.277	.294	.319	.364
7	.247	.258	.276	.300	.348
8	.233	.244	.261	.285	.331
9	.223	.233	.249	.271	.311
10	.215	.224	.239	.258	.294
11	.206	.217	.230	.249	.284
12	.199	.212	.223	.242	.275
13	.190	.202	.214	.234	.268
14	.183	.194	.207	.227	.261
15	.177	.187	.201	.220	.257
16	.173	.182	.195	.213	.250
17	.169	.177	.189	.206	.245
18	.166	.173	.184	.200	.239
19	.163	.169	.179	.195	.235
20	.160	.166	.174	.190	.231
25	.142	.147	.158	.173	.200
30	.131	.136	.144	.161	.187
$n > 30$	$.736/\sqrt{n}$	$.768/\sqrt{n}$	$.805/\sqrt{n}$	$.886/\sqrt{n}$	$1.031/\sqrt{n}$

**Table A23 Table of Critical Values for the Kolmogorov–Smirnov Test
for Two Independent Samples**

		One-tailed	.10	.05	.025	.01	.005
		Two-tailed	.20	.10	.05	.02	.01
n_1	n_2						
3	3		.667	.667			
3	4		.750	.750			
3	5		.667	.800	.800		
3	6		.667	.667	.833		
3	7		.667	.714	.857	.857	
3	8		.625	.750	.750	.875	
3	9		.667	.667	.778	.889	.889
3	10		.600	.700	.800	.900	.900
3	12		.583	.667	.750	.833	.917
4	4		.750	.750	.750		
4	5		.600	.750	.800	.800	
4	6		.583	.667	.750	.833	.833
4	7		.607	.714	.750	.857	.857
4	8		.625	.625	.750	.875	.875
4	9		.556	.667	.750	.778	.889
4	10		.550	.650	.700	.800	.800
4	12		.583	.667	.667	.750	.833
4	16		.563	.625	.688	.750	.812
5	5		.600	.600	.800	.800	.800
5	6		.600	.667	.667	.833	.833
5	7		.571	.657	.714	.829	.857
5	8		.550	.625	.675	.800	.800
5	9		.556	.600	.689	.778	.800
5	10		.500	.600	.700	.700	.800
5	15		.533	.600	.667	.733	.733
5	20		.500	.550	.600	.700	.750
6	6		.500	.667	.667	.833	.833
6	7		.548	.571	.690	.714	.833
6	8		.500	.583	.667	.750	.750
6	9		.500	.556	.667	.722	.778
6	10		.500	.567	.633	.700	.733
6	12		.500	.583	.583	.667	.750
6	18		.444	.556	.611	.667	.722
6	24		.458	.500	.583	.625	.667
7	7		.571	.571	.714	.714	.714
7	8		.482	.589	.625	.732	.750
7	9		.492	.556	.635	.714	.746
7	10		.471	.557	.614	.700	.714
7	14		.429	.500	.571	.643	.714
7	28		.429	.464	.536	.607	.643
8	8		.500	.500	.625	.625	.750
8	9		.444	.542	.625	.667	.750
8	10		.475	.525	.575	.675	.700
8	12		.458	.500	.583	.625	.667
8	16		.438	.500	.563	.625	.625
8	32		.406	.438	.500	.563	.594

**Table A23 Table of Critical Values for the Kolmogorov–Smirnov Test
for Two Independent Samples (continued)**

		One-tailed	.10	.05	.025	.01	.005
		Two-tailed	.20	.10	.05	.02	.01
n_1	n_2						
9	9		.444	.556	.556	.667	.667
9	10		.467	.500	.578	.667	.689
9	12		.444	.500	.556	.611	.667
9	15		.422	.489	.533	.600	.644
9	18		.389	.444	.500	.556	.611
9	36		.361	.417	.472	.528	.556
10	10		.400	.500	.600	.600	.700
10	15		.400	.467	.500	.567	.633
10	20		.400	.450	.500	.550	.600
10	40		.350	.400	.450	.500	.576
11	11		.454	.454	.545	.636	.636
12	12		.417	.417	.500	.583	.583
12	15		.383	.450	.500	.550	.583
12	16		.375	.438	.479	.542	.583
12	18		.361	.417	.472	.528	.556
12	20		.367	.417	.467	.517	.567
13	13		.385	.462	.462	.538	.615
14	14		.357	.429	.500	.500	.571
15	15		.333	.400	.467	.467	.533
16	16		.375	.375	.438	.500	.563
17	17		.353	.412	.412	.471	.529
18	18		.333	.389	.444	.500	.500
19	19		.316	.368	.421	.473	.473
20	20		.300	.350	.400	.450	.500
21	21		.286	.333	.381	.429	.476
22	22		.318	.364	.364	.454	.454
23	23		.304	.348	.391	.435	.435
24	24		.292	.333	.375	.417	.458
25	25		.280	.320	.360	.400	.440
For all other sample sizes			1.07K	1.22K	1.36K	1.52K	1.63K

Where: $K = \sqrt{\frac{n_1 + n_2}{n_1 n_2}}$